MODELS OF INFORMATION, TRADING AND VOLATILITY FOR STOCK RETURNS

By

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MODELS OF INFORMATION, TRADING AND VOLATILITY
FOR STOCK RETURNS

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In this dissertation, I examine how information flow affects daily stock return volatility. First I use the popular generalized autoregressive conditional heteroskedastic (GARCH) process to estimate the conditional variance of daily stock returns. I find that information flow, approximated by trading activity, has significant power in explaining the conditional volatility. Even controlling for information flow does not cause the autocorrelation of conditional variance to vanish as documented by other studies.

Even though the GARCH model satisfactorily describes stock returns and links the volatility with the flow of information, it leaves a significant part of the kurtosis unexplained. This is due to the GARCH model's inability to capture discrete changes in stock prices. Also, a descriptive model like GARCH

can not intuitively interpret the association of information flow, trading activity and stock volatility. Therefore, a more sophisticated model is required to explore the links among them.

The mixed jump-diffusion model provides a natural and intuitive way to capture both smooth changes and discrete jumps in stock prices. I use this model to separately estimate the relative importance of private information, public information, noise, and trading activity in determining daily stock return volatility. In contrast to some early studies, I find that the volatility is mainly due to public information rather than private information. Discrete jumps account for 97% of total volatility for small firms and only 68% for large firms. Further, trading is associated with a significant proportion of the volatility. This is consistent with the hypothesis that differences in opinion generate significant trading and volatility. Finally, the negative relation between the adverse selection component of the bid-ask spread and the trading related diffusion variance suggests that trading is dominated by liquidity traders rather than informed investors.

CHAPTER 1
INTRODUCTION

Many theoretical financial models are based on the assumption that stock returns are normally distributed with stationary parameters. Researchers have long recognized, however, that stock returns exhibit characteristics that differ from a sample of independent and identically distributed normal variates. The empirical evidence shows that daily stock returns are leptokurtic (fat tails relative to the normal distribution), skewed, and peaked at the mean.

Further more, volatility clustering is also widely documented for daily stock returns. The clustering of volatility indicates autocorrelation of volatility and different statistical models have been developed to accommodate and account for the autocorrelation. The autoregressive conditional heteroskedasticity (ARCH) and the generalized ARCH (GARCH) models (Engle, 1982; Bollerslev, 1986) are the well known ones. The ARCH model presumes that forecasts of the variance can be improved by using recent information. In particular, volatility clustering implies that big surprises in either direction will boost volatility. Forecasts of volatility provided by models such as ARCH and GARCH, which recognize this fact, will generally be more accurate than those which do not.

ARCH and GARCH models have been applied to many time series--e.g., exchange rates, inflation rate and stock returns--to capture serial correlation in conditional variances. However, the underlying cause of the serial correlation is poorly understood. For stock returns, interpretation and explanatory variables for the observed ARCH effects have been proposed on both the macro and micro levels. On the macroeconomic level, relevant economic variables and events, such as nominal interest rates (Campbell, 1987; Glosten, Jagannathan, and Runkle, 1991), M1 money supply (Engle and Rodrigues, 1989), dividend yields, business cycle and financial crisis (Schwert, 1989), are suggested to affect stock volatility. On the micro level, Lamoureux and Lastrapes (1990) argue that the ARCH effect reflects clustering in trading volume. By introducing the contemporaneous trading volume in the conditional variance equation of a GARCH(1,1) model for individual stock returns, they show that the lagged conditional variance is no longer significant. Daily stock returns, they suggest, that are generated by a mixture of distributions, in which the rate of daily information arrival is the stochastic mixing variable. The presence of the GARCH effects simply indicates the time series properties (e.g., serial correlation) of this mixing variable. They find that the variance of daily price increments is heteroskedastic and specifically, positively related to the rate of daily information arrival. In particular, they show that GARCH effects vanish when trading volume (a proxy for information arrival) is included as an explanatory variable in

the conditional variance equation. Lamoureux and Lastrapes (1990) effectively relate trading to daily stock return volatility. Though an important step towards understanding GARCH effects and stock return volatility, their study is based on a small set of stocks over different sample periods and the stock returns are based on the transaction (closing) prices. As pointed out by Roll (1984), the bid-ask error in transaction prices may cause spurious volatility and autocorrelation of volatility. To avoid this, I investigate the GARCH effects in the daily stock returns computed from the averages of bid and ask quotes, which do not contain the spurious volatility induced by the bid-ask bounce. I examine the volatility of daily stock returns for all firms traded on Nasdaq-NMS which have the necessary data in the period from March 3, 1986 to December 31, 1991. I use both trading volume and the number of trades (transactions) to approximate the information flow. Intuitively, the number of trades should be a better proxy for the number of information events. By conditioning the variance of the daily stock returns on both the number of trades and trading volume, I can compare the information content of the number of trades with trading volume.

In their study, Lamoureux and Lastrapes (1990) recognize the importance of information in generating volatility, and they propose an intuitive way to approximate the information flow with daily trading volume. However, the interactions among the volatility, trading and information are difficult to explore with GARCH models. Particularly, GARCH model provides no way to

investigate how public and private information determine daily stock return volatility. Also, the discontinuities found in stock prices are not captured by the ARCH/GARCH models. In order to improve our understanding of stock return volatility and to identify the sources of stock return volatility, I employ a new approach based on the mixed jump-diffusion model to examine the links among information, trading activity and volatility. The mixed jump-diffusion model can directly estimate the relative importance of public and private information in determining stock return volatility and explore the process through which the information is incorporated into prices.

The mixed jump-diffusion model was proposed by Press (1967) to capture discrete changes in prices in addition to continuous changes. In his model, the price of a security is assumed to be the sum of a continuous diffusion process, that is, geometric Brownian motion, and a jump process. The diffusion process captures small and smooth movements of stock price changes while the jump process models the discrete price changes caused by unanticipated important news. The number of arrivals of such information per unit of time is distributed as a Poisson process and the size of each jump associated with the information is lognormally distributed. The mixed jump-diffusion process is also called the "compound events" process. This mixed process may be skewed and leptokurtic. Therefore, it is consistent with the empirical findings for daily stock returns.

By conditioning both the diffusion and the jump processes on trading activity, I can decompose the total volatility into

trading and non-trading related components. I assume the jump process is induced by unanticipated public information while the diffusion process is generated by both noise and private information. The ratio of the variation of diffusion process to jump process yields the relative importance of private and public information in determining the daily stock return volatility. French and Roll (1986) examine the same problem by comparing the variance ratio of non-trading period to trading period. Under the assumption that the public information flow is constant, they conclude that private information is the principle factor behind high trading-time variances. French and Roll (1986) define the non-trading period as the normal business days but the New York and American Stock Exchanges are closed. Jones, Kaul and Lipson (1994a) use a different methodology. They define the non-trading period as the period in which there are no transactions at all while the exchanges are open. It means that investors endogenously decide not to trade during the "non-trading" period. By comparing the variance ratio of non-trading to trading periods, they claim that public information is a significant determinant of volatility, but private information still plays a primary role. The problem with their study is that there rarely exist "non-trading" periods for large, actively traded stocks. Therefore, they pick those days in which there are only 1 or 2 trades as "non-trading" period. This methodology definitely introduces biases into their results. On the other hand, I impose no assumptions on the interpretation on trading and non-trading. The mixed jump-diffusion model conditioned on

trading volume or the number of trades provides a direct and intuitive way to investigate the role of trading activity in determining stock price changes.

Copeland and Galai (1983) note that the spread must be wider to protect market markers (specialists) from the losses from trading with the "informed" traders. If information arrives sequentially, the more informed investors will trade first. Since informed investors who acquire good (bad) news are willing to bid (ask) a higher (lower) price to buy (sell) stocks, the adverse selection component of the bid-ask spread (in turn, the spread itself) may change according to the trading behavior of the participants who possess private information. To infer the importance of the private information and noise in trading related volatility, I examine the relation between the adverse selection component of the bid-ask spread and trading activities.

The identification of the sources of volatility is an important issue in understanding the nature of excess volatility of financial markets. If stock price volatility is simply a result of significant information flowing into the stock market and being incorporated into equilibrium prices, Grossman (1976) argues that stock price volatility does not necessarily mean social welfare loss. It is just a "normal" response to the economic fundamental factors implied by the information. Therefore, there is no need to contain the volatility. On the other hand, if noise is the dominant force in generating stock price volatility, higher volatility reflects more noise trading

and/or a smaller ability or willingness of rational agents to counteract it. De Long, Schleifer, Summers and Waldmann (1989) suggest that this would lead to less efficient asset pricing and a loss of social welfare.

In this dissertation, I find that the GARCH model satisfactorily describes daily stock returns. But a significant part of the observed kurtosis of stock returns is still not explained. I also find that the information flow which is approximated by both the number of trades and trading volume has significant power in explaining conditional volatility. However, the autocorrelation of conditional variance does not vanish as documented by other studies even after controlling for information flow by using either the number of transactions or trading volume.

Based on the estimation results of the mixed jump-diffusion model, I find that most of the volatility is due to public information rather than private information. This is in contrast to early studies by French and Roll (1986) and Jones, Kaul and Lipson (1994a). Discrete jumps account for 97 percent of total volatility for small capitalization firms and only 68 percent for large firms. Further, trading is associated with a significant proportion of daily stock return volatility. This is consistent with the hypothesis that differences in opinions regarding public information generate significant trading and volatility. The impact of differences in opinions is more pronounced for large firms. Finally, the negative relationship between the adverse selection component of the bid-ask spread

and the trading related diffusion variance suggests that trading is dominated by liquidity (noise) traders rather than informed investors.

This dissertation is organized as follows. In Chapter 2, I examine the validity of the mixture-of-distributions hypothesis in explaining the GARCH effects. The relative performance of the number of trades and trading in correcting the skewness and kurtosis is compared. In Chapter 3, I investigate the effects of information on the stock return volatility by employing the mixed jump-diffusion model. In this chapter, I also examine the role of trading, the relative importance of public and private information in determining the volatility. In Chapter 4, I summarize the findings and suggest areas for future research.

CHAPTER 2
CONDITIONAL STOCK RETURN VOLATILITY AND TRADING ACTIVITY

2.1 Introduction

For many years, financial theoretical models assumed that stock returns are normally distributed with stationary parameters. However, Mandelbrot (1963), Fama (1965), Westerfield (1977), and Kon (1984) find that the daily stock returns are more leptokurtic than predicted from a sample of independent and identically distributed normal variates. In addition, the returns are skewed and peaked at the mean. Many studies also identify volatility clustering--large changes tend to be followed by large changes of either sign. Further, several studies also document significant discrete changes in stock prices. Several widely used option pricing models (e.g., Black and Scholes, 1973) produce estimates that systematically differ from actual market prices. Specifically, the Black-Scholes model consistently underprices call options that are near to expiration, on stocks of low volatility, or deep out of the money. The biased predictions of the Black-Scholes option pricing model are believed to be rooted in the departure of the distribution of the actual underlying stock returns from the assumption of continuous normality.

Over the years, many studies have proposed alternative models to explain the observed characteristics of stock returns. A scaled t-distribution was proposed by Paretz (1972) while Rosenberg (1972) suggested the stable lognormal with

nonstationary variance. Mandelbrot (1973) proposed a Paretian model.

Clark (1973), Blattberg and Gonedes (1974), Epps and Epps (1976), Tauchen and Pitts (1983), Kon (1984), and Gallant, Hsieh and Tauchen (1988) consider finite mixture-of-normal-distributions models. The finite mixture-of-normal-distributions models suggest an intuitive interpretation for excess kurtosis of daily stock returns by assuming the daily price changes are sampled from a set of distributions that are characterized by different variances. This is usually called the "mixture of distributions hypothesis" (MDH).

The mechanism of price movements under MDH is as follows. The daily price change is the sum of a variable number n of independent intra-day price changes. For a constant n, the aggregate price change over a day is approximately normally distributed with variance being proportional to n according to the Central Limit Theorem. However, a varying n will induce the distribution of stock price changes to be subordinated to the distribution of the n. If n is the number of significant information arrivals, MDH links information flow with stock price volatility. Since the arrival of information, especially private information, is unobservable, trading activities such as trading volume and the number of trades are used to approximate information flow. More importantly, previous studies have reported a close relationship between volatility and trading volume. The recent episodes of high price volatility coupled

with heavy trading volume in equity markets during the "market breaks" of 1987 and 1989 are some examples.

More recently, Engle (1982) proposed the autoregressive conditional heteroskedasticity (ARCH) process to describe serial correlation of the variance of many stochastic variables. The ARCH model imposes an autoregressive structure on conditional variance, allowing volatility shocks to persist over time. Specifically, the conditional error distribution is normal, with conditional variance equal to a linear function of past squared errors. The generalized ARCH introduced by Bollerslev (1986) allows the current conditional variance to be a function of past conditional variances in addition to the squared past errors. In recent years, numerous studies have applied the ARCH model of Engle (1982) and the generalized ARCH (GARCH) model of Bollerslev (1986) to capture the documented clustering of volatility in stock returns. Particularly, French, Schwert, and Stambaugh (1987), Akgiray (1989), Connolly (1989), Pagan and Schwert (1990), Lamoureux and Lastrapes (1990), and Kim and Kon (1994) have successfully applied the ARCH and GARCH models to analyze stock return series.

The large body of research on ARCH models demonstrates that popularity and success of these models. This success is due to their simplicity and its ability to capture time varying volatility and leptokurtosis. However, the origins of the ARCH or GARCH effects remain an open question. Since the mixture-of-distributions hypothesis (MDH) provides an intuitive way to interpret the time-series properties of stock returns captured

by ARCH/GARCH models, it is useful to investigate the links between these two frameworks. Essentially, I will examine the GARCH effects in daily stock returns after controlling for the information flow. Due to the difficulty of observing the true information flow, trading activity is used as a proxy. If trading activity is a good proxy for information flow and MDH is true, the GARCH effects should vanish. This methodology follows the study of Lamoureux and Lastrapes (1990).

In this chapter, I examine the GARCH effects for 845 stocks traded on Nasdaq-NMS for the period from March 3, 1986 to December 31, 1991. The hypothesis that ARCH effects are generated by a mixture of distributions subordinated to information flow is investigated.

Previous studies have used trading volume to study the links between trading activity and stock volatility. However, Jones, Kaul and Lipson (1994b) suggest that the positive volatility-volume relation documented by numerous researchers actually reflects the positive relation between volatility and the number of transactions. Thus, it is the occurrence of trades per se, and not their size, that generates volatility; trade size has no information beyond that contained in the frequency of transactions. This proposition is also investigated in this chapter.

Section 2.2 presents the ARCH, GARCH and the mixture-of-distributions models. Section 2.3 describes the data used in this dissertation. Section 2.4 summarizes the empirical findings. Section 2.5 concludes the chapter.

2.2 Models

To represent a series R_t with time varying volatility, Engle (1982) proposed the autoregressive conditional heteroskedasticity (ARCH) model of order q,

$$\begin{aligned} R_t &= \alpha_0 + \varepsilon_t, \\ \varepsilon_t | I_{t-1} &\sim N(0, h_t^2), \\ h_t^2 &= \alpha_1 + \alpha_2 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2, \end{aligned} \tag{2.1}$$

where, I_{t-1} is the information available at time t, particularly, squared past error terms. Conditional on I_{t-1}, ε_t is assumed to be identical, independent and normally distributed with variance h^2_t.

The ARCH model is attractive because the mean and variance processes are estimated jointly in addition to the fact that there is no unpredictable component of volatility at time t after conditioning on the variation ε_{t-1} at time $t-1$. Non-negativity of the α'_is is required for the variance to be non-negative. In addition, $\sum_{i=1}^{q} \alpha_i$ must be less than 1 to guarantee that R_t is stationary. For an ARCH(1) model, it is easy to see that an increase in h^2_{t-1} will cause an increase in h^2_t. Therefore it captures the clustering of volatility.

Bollerslev (1986) extended Engle's (1982) ARCH model by allowing the conditional variance to be an ARMA process. In Bollerslev's generalized ARCH or GARCH model, the conditional error process is

$$\varepsilon_t | I_{t-1} \sim N(0, h_t^2),$$
$$h_t^2 = \alpha_1 + \sum_{i=2}^{q+1} \alpha_i \varepsilon_{t+1-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}^2 + \sum_{l=1}^{w} \gamma_l x_{t,l}, \qquad (2.2)$$

with $\alpha_i > 0, \beta_j > 0, \sum_i \alpha_i + \sum_j \beta_j < 1$, where $x_{t,l}$ are exogenous variables, such as unemployment rate, consumer price index and dummy variables of day of the week. This GARCH(p,q) model allows for both autoregressive and moving average components in the heteroskedastic variance. The conditional variance of the series will be larger if the weighted average of h^2_{t-1} and past ε^2_{t-1} are larger. If we set p=0 and l=0, equation 2.2 is reduced to the ARCH(q) model given in equation 2.1. The benefit of the GARCH model is very clear: a high-order ARCH model may have a more parsimonious GARCH representation that is much easier to identify and estimate.

To estimate parameters $\theta = (\alpha_0, \alpha_1, \ldots, \alpha_q, \beta_1, \ldots, \beta_p, \gamma_1, \ldots, \gamma_l)$ of a GARCH(p,q) process, under the assumption that the residual ε_t are conditionally normally distributed, given a sample of daily stock returns $R_1, \ldots, R_T$, the average log-likelihood function L is then given by

$$L = \frac{1}{T} \sum_{t=1}^{T} l_t \qquad (2.3)$$

$$l_t = c - \frac{1}{2} \log h_t^2 - \frac{1}{2} \frac{e_t^2}{h_t^2} \qquad (2.4)$$

where l_t are the log likelihood function of observation t, c is a constant. Following the first order condition, the estimates of

the parameters θ that maximize the likelihood are computed by using the following recursive procedure,

$$\theta^{t+1} = \theta^{t} + \left[\sum_{t=1}^{T} \frac{\partial l_t}{\partial \theta} \times \frac{\partial l_t}{\partial \theta'}\right]^{-1} \sum_{t=1}^{T} \frac{\partial l_t}{\partial \theta}. \qquad (2.5)$$

The assumption of normally distributed residuals is usually not valid for stock returns since the tails of the distributions are too fat. In GARCH models only conditional normality is required. Conditionally normal error terms are fully consistent with fat-tailed data. However, the results of most empirical studies indicate that even the assumption of conditional normal distribution is violated, as the standardized residuals still differ from normal variates. The GARCH estimates are still consistent, but their standard errors are not consistent. This type of maximum likelihood is called quasi maximum likelihood. The inconsistency of the standard error can be corrected by a method suggested by Bollerslev and Wooldridge (1992). In this study, I report the robust standard errors by employing the method of Bollerslev and Wooldridge (1992).

To motivate the empirical tests of the validity of the MDH's interpretation of the ARCH effect, let r_i be the moment equilibrium return of the securities at time i. Following the mixture-of-distributions hypothesis, we have the security return R_t over a day

$$R_t = \sum_{i=1}^{n_t} r_i, \qquad (2.6)$$

where n_t represents the number of events that generates important information to the pricing of securities, or could be thought of as the rate at which information flows into the stock market. This model is proposed by Mandelbrot and Taylor (1967), Clark (1973), Westerfield (1977), Tauchen and Pitts (1983), Harris (1987), and Lamoureux and Lastrapes (1990). They suggest that daily returns are generated by a subordinated stochastic process, in which R_t is subordinated to r_i and n_t is the directing process.

If r_i are identical and independent random variables with mean zero and variance σ^2 and n_t is large enough, by the Central Limit Theorem, the conditional distribution of R_t is given by

$$R_t|n_t \sim N(\alpha_o, \sigma^2 n_t) . \qquad (2.7)$$

Following the above conditional distribution of R_t we would expect the positive correlation among the conditional variance of daily stock returns, the trading activities such as the trading volume and the number of trades. It is because they are driving by the same mixing variable n_t.

Suppose that an autocorrelated series of events happens, they induce the change of the equilibrium returns of securities as traders adjust their portfolios in response to the events. So we will see the co-movement of the volatility of returns and trading activity. Given the above conditional distribution of R_t, we would expect the conditional variance to be positively autocorrelated if the mixing variable n_t is positively autocorrelated. Therefore, the GARCH effects are explained by this time dependence in the rate of evolution of intra-day equilibrium returns. We have

$$h_t^2 = Var(R_t \mid I_t) = \sigma^2 n_t , \tag{2.8}$$

and

$$n_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i n_{t-i} . \tag{2.9}$$

Substitute equation (2.9) into (2.8):

$$h_t^2 = \sigma^2 (\gamma_0 + \sum_{i=1}^{p} \gamma_i n_{t-i} + u_t) = \sigma^2 (\gamma_0 + u_t) + \sum_{i=1}^{p} \gamma_i h_{t-i}^2 . \tag{2.10}$$

Equation 2.10 captures the persistence in conditional variance that can be picked up by a GARCH model. n_t is assumed to be a random variable, the innovations in n_t cause the variations in the conditional variance of daily returns. To eliminate this kind of variation of stock returns we could normalize it by dividing R_t by the square root of n_t. In practice, n_t is not observable, a proxy such as the number of trades NTS_t and trading volume VOL_t has to be used. In fact, Tauchen and Pitts (1983) model volume and price change as being a joint function of information flow. If their model is correct, the normalized return $R_t / \sqrt{NTS_t}$ should be less kurtotic and more symmetric than R_t. Previous studies on the impacts of information on prices of securities have used trading volume as a proxy. Part of the reason for using trading volume instead of the number of transactions was the lack of data. However, intuition tells us that the mixing variable of information arrival will coincide with the transaction itself but not the size of the transaction.

2.3 Data

The data used in this study consists of firms that are traded on the Nasdaq-NMS system. The firms were chosen from the Center for Research of Security Price (CRSP) master tapes so that they had daily data (transaction prices, bid-ask prices, the number of trades and trading volume) for the period from March 3, 1986, to December 31, 1991. Trading on the Nasdaq-NMS system was initiated in 1982. However, during the early period the trading was limited to only actively traded stocks. Further, the bid-ask spread data is not reported for February 1986. Therefore, in this study I employ daily data from March 3, 1986, through December 31, 1991. However, due to the unusual volatility that was experienced by all the stocks during the October 1987, we eliminate all the observations from October 15, 1987, through October 31, 1987, in our estimation. This data period is identical to the one employed by Jones, Kaul and Lipson (1994a, 1994b). There were 845 firms that had all the required daily prices and trading data over the sample period consisting of 1464 trading days. In addition to price, bid-ask spread and trading data, we also obtained the number of outstanding shares, the number of market makers, and the market value of equity at the beginning (March 3, 1986) and at the end (December 31, 1991) of the sample period.

The estimates of parameters for the GARCH models are all based on returns calculated by using the average of the bid and ask quotes at the end of the day. I use the average of the bid-ask quotes instead of the transaction prices because volatility

estimates based on transaction prices are contaminated by the bias due to bid-ask bounce (see Roll, 1984). Further, Kaul and Nimalendran (1990) document that the volatility induced by bid-ask bounce can be as high as fifty percent for small market capitalization firms traded on the Nasdaq-NMS market. Jones, Kaul and Lipson (1994a) also find that the bid-ask bounce can lead to substantial biases in the variance estimates and the variance ratios. Returns based on the average of bid and ask on the other hand will not have any noise caused by due to bid-ask errors.

However, quote returns on Nasdaq-NMS are generally sticky, and Geraghty (1992) finds that for large number of Nasdaq firms the quotes remain unchanged from one day to the other, even if there is trading. This stickiness can lead to lagged adjustment of prices to market wide or firm specific information. To control for the effect of quote stickiness and lagged adjustment of prices we follow the procedure employed by Jones, Kaul and Lipson (1994a). That is we first estimate the following model.

$$R'_{it} = \sum_{k=1}^{5} \alpha_{ik} D_{kt} + \sum_{j=0}^{5} \beta_{ij} R_{m(t-j)} + \sum_{l=1}^{5} \theta_{il} R'_{i(t-l)} + R_{it}, \qquad (2.11)$$

where R'_{it} is the return on stock 'i' at time 't', R_{mt} is the return on the value weighted market portfolio, D_{kt} is a dummy variable for the day of the week k. The day of the week dummy variable is used to control for differences in expected returns for different days of the week that have been documented by several studies. Jones, Kaul and Lipson (1994a) argue that the

five lags for the returns and for the market as well as the contemporaneous market will control for partial adjustment as well as any private information revealed through trading in another related stock.

We estimate the parameters of the model described by Equation 2.2 for all the stocks by using the residuals R from equation 2.11

Some descriptive statistic variables are reported in Table 2.1. Only the means of the statistics for the five market value weighted portfolios and all firms are reported. The skewness of the stock returns R' based on the average of bid and ask quotes and the adjusted returns $R,$, which is the residuals from equation 2.11 are all significantly different from 0. Note that the standard error of skewness is equal to $\sqrt{\frac{6}{n}}$, where n is the number of observations. For a sample of 1464, the standard error is equal to 0.064. We find that the skewness decreases with the firm size. We also report the skewness of returns R' and the adjusted return R after controlling for the number of trades NTS and the trading volume VOL. The trading volume used in this study is sometimes called the turnover volume, that is, the number of trading shares divided by the number of outstanding shares. After the adjustment, the skewness is lower for all firms. For portfolios 3 and 5, the residual terms from equation 2.11 after being adjusted by the trading volume are no longer significantly skewed. There are similar regularities for

kurtosis, the only difference is that the number of trades is better in terms of reducing the excess kurtosis. These results suggest that trading volume contains information which causes skewness while the number of trades is more closely related to fat tails. Therefore, we would expect the number of trades will provide more explanatory power for the leptokurtosis of stock returns. The correlation among R^2, R'^2, *VOL and NTS* are presented in Table 2.2. The square of R and R' is used to approximate the daily stock return variance. The market values are also reported. The market value is the average of the market values at the beginning and the end of the sample period. The correlation between the squares of returns and the number of trades is significantly larger than the correlation between trading volume and squared returns. Figure 2.1 is the histogram of the stock returns. Figure 2.2 demonstrates the clustering of volatility of stock returns.

2.4 Results

The maximum likelihood estimates of the parameters of the GARCH(1,1) process are reported in Tables 2.3 and 2.4. After estimating the parameters for all 845 stocks, we calculate the means of each estimate for five portfolios (each consists of 169 stocks, the portfolios are ranked by their market values from small to large) and for all firms. The means of estimates are presented in Panel A. Panel B lists the number of estimates which are significantly different from zero at 5 percent level. The number of estimates which are positive is also reported.

Table 2.1 Descriptive Statistics

Panel A: Mean

Portfolio	$Rx10^5$	$R'x10^4$	VOL	NTS	$R/NTS^{1/2} x\ 10^4$	$R/VOL^{1/2}\ x10^4$
1 (small)	1.39	-0.03	2.57	5.14	-3.29	-9.72
2	4.65	2.90	3.44	9.54	-2.51	-9.16
3	3.48	2.68	3.21	13.28	-1.80	-7.75
4	3.77	4.90	3.30	18.77	-1.32	-6.64
5 (large)	0.43	5.99	3.82	62.55	-0.92	-5.35
All	2.75	3.29	3.27	21.86	-1.97	-7.72

Panel B: Variance

Portfolio	$Rx10^4$	$R'x10^4$	VOL	NTS	$R/NTS^{1/2}\ x10^5$	$R/VOL^{1/2}\ x10^4$
1 (small)	8.86	9.59	56.39	71.31	17.64	7.68
2	7.73	8.65	119.18	192.12	8.34	6.59
3	6.14	7.05	45.77	374.31	5.39	5.16
4	4.27	5.17	42.76	1045.23	2.71	3.41
5 (large)	3.24	4.32	31.13	10069.9	0.92	2.01
All	6.05	6.95	59.05	2350.58	7.00	4.97

Panel C: Skewness

Portfolio	R	R'	VOL	NTS	$R/NTS^{1/2}$	$R/VOL^{1/2}$
1 (small)	1.23	1.11	8.71	4.28	0.13	-0.15
2	1.20	0.94	7.43	4.10	0.33	0.28
3	0.82	0.55	8.04	3.82	0.20	-0.03
4	0.76	0.42	7.19	3.45	0.28	0.16
5 (large)	0.50	0.19	5.82	3.27	0.15	0.05
All	0.90	0.64	7.44	3.79	0.22	0.06

Panel D: Excess Kurtosis

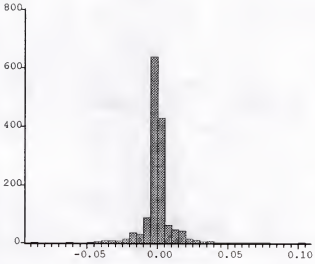
Portfolio	R	R'	VOL	NTS	$R/NTS^{1/2}$	$R/VOL^{1/2}$
1 (small)	25.48	26.59	136.33	37.14	12.74	19.79
2	24.79	26.17	102.86	34.21	12.21	23.07
3	19.90	21.78	123.78	30.04	10.73	21.40
4	17.46	19.79	107.29	26.64	6.58	12.77
5 (large)	10.75	14.34	75.42	24.93	2.63	5.93
All	19.67	21.74	109.14	30.59	8.98	16.59

Note: R are the residuals from the equation 2.11, R' are the stock returns based on the average of bid-ask quotes, VOL is the trading volume, NTS is the number of trades. The statistics are the mean of statistics for each value weighted portfolio (169 stocks) and all 845 stocks. Each portfolio consists of 169 stocks.

Table 2.2 The Correlation Coefficients

The mean of correlation coefficients for each value weighted portfolio (consisting of 169 stocks) and all the 845 stock are listed. Each portfolio consists of 169 stocks.

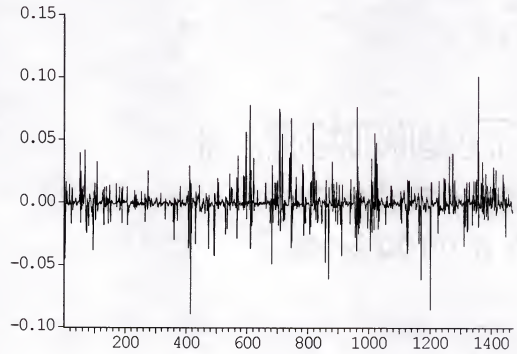
Portfolio	(R^2, VOL)	(R^2,NTS)	(R'^2,VOL)	(R'^2,NTS)	(VOL,NTS)
1 (small)	0.21	0.34	0.21	0.35	0.57
2	0.22	0.35	0.21	0.35	0.62
3	0.21	0.37	0.20	0.37	0.58
4	0.22	0.40	0.21	0.40	0.57
5 (large)	0.26	0.44	0.23	0.43	0.59
All	0.22	0.38	0.21	0.38	0.59



Series: Daily Stock Returns
Sample 3/3/1986--12/31/1991
Observations 1470

Mean	3.40E-09
Median	-0.000522
Maximum	0.100652
Minimum	-0.089113
Std. Dev.	0.011813
Skewness	0.749346
Kurtosis	19.43767
Jarque-Bera	16687.14
Probability	0.000000

Figure 2.1 Histogram and Statistics for Dialy Stock Returns Based on the Averages of Bid and Ask Quotes



Sample: 3/3/86--12/31/91

Figure 2.2 Daily Stock Returns Based on the Averages of Bid and Ask quotes

For 765 out of 845 stocks, the coefficient of the lagged conditional variance is significant. For 672 stocks, the coefficient of the square of past error is also significant. The sum of coefficients of lagged conditional variance and the square of past error term is a measure of the persistence of the conditional volatility. The average of this sum for 845 stocks is 0.85, which is significantly smaller than the 0.97 reported by Akgiray (1989). The results in Table 2.3 indicate that the persistence of volatility does not vary with firm size. The constant coefficient in the conditional equation, α_1, is about 1.09×10^{-4}. This shows that the conditional variance are changing overtime. In Table 2.4, we report the maximum likelihood estimates of the parameters of the GARCH(1,1) process for the 20 largest firms. In addition, for each firm, the maximum likelihood function value, skewness, excess kurtosis, and the Jarque-Bera statistic for normality of the standardized residuals are also reported. For all stocks but two, the coefficient of the square of past error term is significant at the 5 percent level. For only one stock, the lagged conditional variance is not significant. However, the null hypothesis of normality of standardized residuals is rejected for all twenty largest stocks.

Table 2.5 and 2.6 report the parameter estimates of the GARCH(1,1) model with the number of trades in the conditional equation. For 824 out 845 stocks, the number of trades is significant in explaining the conditional volatility. The persistence measure of conditional volatility is reduced from

For 765 out of 845 stocks, the coefficient of the lagged conditional variance is significant. For 672 stocks, the coefficient of the square of past error is also significant. The sum of coefficients of lagged conditional variance and the square of past error term is a measure of the persistence of the conditional volatility. The average of this sum for 845 stocks is 0.85, which is significantly smaller than the 0.97 reported by Akgiray (1989). The results in Table 2.3 indicate that the persistence of volatility does not vary with firm size. The constant coefficient in the conditional equation, α_1, is about 1.09×10^{-4}. This shows that the conditional variance are changing overtime. In Table 2.4, we report the maximum likelihood estimates of the parameters of the GARCH(1,1) process for the 20 largest firms. In addition, for each firm, the maximum likelihood function value, skewness, excess kurtosis, and the Jarque-Bera statistic for normality of the standardized residuals are also reported. For all stocks but two, the coefficient of the square of past error term is significant at the 5 percent level. For only one stock, the lagged conditional variance is not significant. However, the null hypothesis of normality of standardized residuals is rejected for all twenty largest stocks.

Table 2.5 and 2.6 report the parameter estimates of the GARCH(1,1) model with the number of trades in the conditional equation. For 824 out 845 stocks, the number of trades is significant in explaining the conditional volatility. The persistence measure of conditional volatility is reduced from

0.85 of the GARCH(1,1) to 0.24 when the number of trades is included. For 369 stocks, the lagged conditional variance is significant while the square of past error term is still significant for 789 stocks. According to Table 2.6, we find that the number of trades is significant for seventeen out of the twenty largest firms. The significant Jarque-Bera statistic rejects the assumption of conditional normality of residuals.

When the trading volume is used to explain the conditional variance, the lagged conditional variance is still significant for 562 stocks. For 761 stocks, the coefficient of the square of past error is significant. The persistence measure is reduced to 0.42 after trading volume is included in the conditional variance equation. For nineteen out of the twenty largest stocks, trading volume has significant power in explaining the conditional variance. All these results are reported in Tables 2.7 and 2.8.

Table 2.9 presents the parameter estimates of the GARCH(1,1) model with both the number of trades and trading volume included in the conditional variance equation. For 514 stocks, the number of trades is still significant in explaining the conditional variance while trading volume is significant in 461 stocks. The persistence measure is 0.49, which is substantially smaller than the one for the GARCH(1,1) model. However, it is much larger than the one for the GARCH(1,1) with the number of trades. For the twenty largest firms, the number of trades and trading volume are both significant in only three stocks. For some stocks, the coefficients of the number trades and trading volume are even negative. This may be due to the

high correlation between the number of trades and trading volume. The parameter estimates for the 20 largest stocks are reported in Table 2.10.

To examine the power of number of trades and trading volume in explaining skewness and leptokurtosis, we report the skewness and kurtosis of the standardized residuals from the GARCH(1,1), the GARCH(1,1) with the number of trades, the GARCH(1,1) with trading volume, and the GARCH(1,1) with both the number of trades and trading volume in Table 2.11.

On average, all four models indicate significant reduction in both skewness and kurtosis of the standardized residuals. The GARCH(1,1) model with trading volume demonstrates the largest reduction in skewness of the standardized residuals. In terms of reducing skewness and kurtosis, the GARCH(1,1) models with either trading volume or the number of trades consistently outperform the GARCH(1,1) model. However, including both the number of trades and trading volume does not help to further reduce the skewness and kurtosis. On the contrary, the GARCH(1,1) with both the number of trades and trading volume does not perform as well as the GARCH(1,1) with only one information proxy.

The significant excess kurtosis of the standardized residuals and the Jarque-Bera statistic for all four GARCH models indicates that the assumption that the residuals are conditionally normally distributed is violated. I use the method proposed by Bollerslev and Wooldridge (1992) to obtain robust standard errors of the maximum likelihood estimates. The reported t-statistic is based on the robust standard errors.

Table 2.3 The GARCH(1,1) Model

$$R_t = \alpha_0 + \varepsilon_t,$$

$$\varepsilon_t | I_{t-1} \sim N(0, h_t^2),$$

$$h_t^2 = \alpha_1 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 h_{t-1}^2,$$

where R_t are the residuals from equation 2.11. The mean of estimates for each value weighted portfolio (169 stocks) is reported in Panel A. The number of estimates which are significant at 5% and the number of estimates which are positive are reported in Panel B.

Panel A

Portfolio	$\alpha_0 x10^4$	$\alpha_1 x10^4$	α_2	α_3	$\alpha_2+\alpha_3$
1 (small)	-4.64	1.24	0.21	0.66	0.86
2	-3.59	1.46	0.21	0.64	0.85
3	-1.59	1.08	0.21	0.67	0.87
4	-1.56	1.01	0.21	0.61	0.82
5 (large)	-0.10	0.66	0.15	0.70	0.85
All	-2.30	1.09	0.20	0.65	0.85

Panel B

	The number of estimates which are significant at 5%				The number of estimates which are positive			
Portfolio	α_0	α_1	α_2	α_3	α_0	α_1	α_2	α_3
1 (small)	19	131	142	156	26	169	169	168
2	24	124	145	148	48	168	169	167
3	11	138	152	157	66	169	169	167
4	12	141	160	151	58	169	169	167
5 (large)	5	138	166	158	78	169	169	167
All	71	672	765	770	276	844	845	836

Table 2.4 The GARCH(1,1) Model
ML Estimates for the 20 Largest Firms

$$R_t = \alpha_0 + \varepsilon_t,$$
$$\varepsilon_t | I_{t-1} \sim N(0, h_t^2),$$
$$h_t^2 = \alpha_1 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 h_{t-1}^2.$$

This table presents the *ML* estimate of the GARCH(1,1) *ML* is the maximum likelihood function value. *S*, *K* and *J-B* are the skewness, kurtosis and Jarque-Bera statistic for adjusted residuals ε_t/h_t, respectively. The t-ratios are reported in parentheses.

	ε^2_{t-1}	h^2_{t-1}	*ML*		
	(*t-ratio*)	(*t-ratio*)	*s*	*k*	*J-B*
1	0.011	0.987	2923.21		
	(1.15)	(86.51)	0.082	18.36	14405.1
2	0.254	0.436	5499.52		
	(1.79)	(2.29)	1.180	26.01	32668.0
3	0.202	0.370	4201.11		
	(2.55)	(3.57)	2.703	37.56	74722.8
4	0.088	0.857	4187.62		
	(3.84)	(21.96)	0.132	5.85	499.32
5	0.067	0.940	5111.12		
	(3.03)	(58.79)	1.750	30.41	46637.4
6	0.213	0.773	4045.01		
	(2.30)	(12.49)	0.710	19.85	17468.5
7	0.299	0.722	3924.41		
	(3.72)	(13.41)	0.796	13.55	6953.99
8	0.045	0.933	4503.91.		
	(2.90)	(42.29)	0.515	7.66	1391.78
9	0.169	0.530	3829.51		
	(3.35)	(3.46)	0.663	10.82	3841.89
10	0.102	0.632	4113.81		
	(2.00)	(4.04)	0.806	14.80	8666.10
11	0.183	0.214	2575.22		
	(3.15)	(1.58)	0.991	7.84	1670.77
12	0.055	0.925	4286.41		
	(3.69)	(41.04)	0.617	5.71	541.34
13	0.061	0.935	4026.81		
	(3.49)	(50.99)	-.178	9.56	2636.89
14	0.070	0.906	2897.92		
	(2.19)	(23.70)	0.715	7.94	1612.89
15	0.068	0.861	3987.22		
	(3.26)	(17.04)	-.017	5.65	428.20
16	0.178	0.806	4463.01		
	(3.45)	(20.18)	-.213	21.69	21357.2
17	0.149	0.732	4627.22		
	(3.49)	(10.98)	-.592	13.64	6999.55
18	0.044	0.939	2932.41		
	(2.91)	(48.85)	0.561	7.87	1523.38
19	0.059	0.890	4076.12		
	(2.19)	(22.20)	0.785	15.17	9193.15
20	0.353	0.509	3019.11		
	(2.70)	(4.76)	2.096	33.31	57205.3

Table 2.5 The GARCH(1,1) with the Number of Trades

$$R_t = \alpha_0 + \varepsilon_t,$$
$$\varepsilon_t | (I_{t-1}, NTS_t) \sim N(0, h_t^2),$$
$$h_t^2 = \alpha_1 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 h_{t-1}^2 + \alpha_4 NTS_t,$$

where R_t are the residuals from equation 2.11. The mean of estimates for each value weighted portfolio (169 stocks) is reported in Panel A. The number of estimates which are significant at 5% and the number of estimates which are positive are reported in Panel B.

Panel A

Portfolio	$\alpha_0 x10^4$	$\alpha_1 x10^5$	α_2	$\alpha_3 x10^2$	$\alpha_4 x10^4$	$\alpha_2+\alpha_3$
1 (small)	-6.62	6.8	0.16	8.67	3.44	0.24
2	-8.09	6.2	0.14	9.89	2.42	0.24
3	-8.85	4.8	0.15	9.42	1.90	0.24
4	-7.09	3.4	0.16	11.33	1.28	0.27
5 (large)	-6.39	2.3	0.13	7.72	1.07	0.20
All	-7.41	4.7	0.15	9.41	2.02	0.24

Panel B

	The number of estimates which are significant at 5%					The number of estimates which are positive				
Portfolio										
1 (small)	91	156	147	70	166	28	168	169	122	167
2	113	145	158	66	163	20	161	169	106	167
3	117	142	163	82	166	15	158	169	87	168
4	115	145	162	83	164	14	152	169	94	167
5 (large)	107	101	159	68	165	14	149	167	87	169
All	543	689	789	369	824	91	788	843	496	838

Table 2.6 The GARCH Model with the Number of Trade
ML Estimates for the 20 Largest Firms

$$R_t = \alpha_0 + \varepsilon_t,$$

$$\varepsilon_t | (I_{t-1}, NTS_t) \sim N(0, h_t^2),$$

$$h_t^2 = \alpha_1 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 h_{t-1}^2 + \alpha_4 NTS_t$$

This table presents the *ML* estimate of the GARCH(1,1) with the number of trades (NTS_t). *ML* is the maximum likelihood function value. *S*, *K* and *J-B* are the skewness, kurtosis and Jarque-Bera statistic for adjusted residuals ε_t/h_t, respectively. The t-ratios are reported in parentheses.

	ε^2_{t-1} (*t-ratio*)	h^2_{t-1} (*t-ratio*)	*NTS* (*t-ratio*)	*ML* *s*	*k*	*J-B*
1	0.092	0.000	0.000039	3122.2		
	(2.79)	(0.00)	(7.80)	0.931	12.04	5196.28
2	0.021	0.212	0.000025	5755.8		
	(0.99)	(1.85)	(5.02)	-1.06	27.08	35670.1
3	0.150	0.600	0.000006	4248.0		
	(2.96)	(4.12)	(0.49)	1.769	26.04	33156.2
4	0.150	0.600	0.000001	4198.8		
	(3.91)	(7.63)	(1.70)	0.165	5.38	353.73
5	0.045	0.329	0.000052	5404.0		
	(1.99)	(4.23)	(4.92)	1.296	22.38	23325.2
6	0.040	-.106	0.000030	4292.1		
	(2.24)	(-1.11)	(2.74)	-1.40	35.25	63959.6
7	0.286	-.011	0.000020	4322.7		
	(3.13)	(-1.11)	(10.38)	0.525	11.15	4125.31
8	0.120	0.584	0.000004	4631.9		
	(2.05)	(6.26)	(4.18)	0.033	5.44	363.19
9	0.108	-.076	0.000014	4155.4		
	(3.36)	(-3.18)	(8.26)	0.240	5.61	430.07
10	0.150	0.600	0.000010	4329.2		
	(4.42)	(8.68)	(3.16)	0.560	9.27	2476.76
11	0.041	-.430	0.000039	2719.2		
	(4.59)	(-8.45)	(8.30)	0.628	6.25	742.47
12	0.150	0.600	0.000000	4316.4		
	(5.19)	(6.55)	(1.48)	0.583	5.66	516.25
13	0.062	-.019	0.000011	4152.5		
	(1.98)	(-0.21)	(9.13)	0.454	6.95	1003.07
14	0.150	0.600	0.000003	2860.1		
	(3.26)	(4.37)	(1.89)	0.502	8.43	1858.91
15	0.150	0.600	0.000000	3985.4		
	(3.56)	(6.12)	(0.51)	-.016	5.20	294.65
16	0.150	0.600	0.000007	4705.2		
	(4.20)	(7.79)	(3.24)	-.056	9.24	2379.76
17	0.150	0.600	0.000004	4715.8		
	(5.05)	(8.37)	(2.35)	-.271	8.69	1991.14
18	0.063	0.907	0.000001	2933.4		
	(3.07)	(31.93)	(1.08)	0.504	7.95	1557.91
19	0.048	0.102	0.000084	4484.6		
	(2.20)	(1.45)	(7.58)	0.469	11.52	4484.53
20	0.329	0.291	0.000043	3358.6		
	(5.90)	(4.59)	(5.38)	-.069	11.20	4106.59

Table 2.7 The GARCH Model with Trading Volume

$$R_t = \alpha_0 + \varepsilon_t,$$
$$\varepsilon_t | (I_{t-1}, VOL_t) \sim N(0, h_t^2),$$
$$h_t^2 = \alpha_1 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 h_{t-1}^2 + \alpha_4 VOL_t,$$

where R_t is the residuals from equation 2.11. The mean of estimates for each value weighted portfolio (169 stocks) is reported in Panel A. The number of estimates which are significant at 5% and the number of estimates which are positive are reported in Panel B.

Panel A

Portfolio	$\alpha_0 \times 10^4$	$\alpha_1 \times 10^5$	α_2	α_3	$\alpha_4 \times 10^5$	$\alpha_2+\alpha_3$
1 (small)	-5.46	6.7	0.14	0.11	11.4	0.25
2	-6.47	5.0	0.14	0.22	4.5	0.36
3	-5.65	3.8	0.14	0.22	2.9	0.36
4	-3.64	1.6	0.15	0.37	1.3	0.51
5 (large)	-2.02	0.3	0.14	0.46	0.4	0.60
All	-4.65	3.5	0.14	0.27	4.1	0.42

Panel B

	The number of estimates which are significant at 5%					The number of estimates which are positive				
Portfolio	α_0	α_1	α_2	α_3	α_4	α_0	α_1	α_2	α_3	α_4
1 (small)	73	139	147	65	161	32	160	168	110	168
2	82	121	147	105	158	31	132	169	103	168
3	88	111	150	110	153	29	128	168	102	168
4	67	105	160	127	140	60	95	169	128	168
5 (large)	34	82	157	155	140	85	68	168	141	168
All	344	558	761	562	752	237	583	842	584	840

Table 2.8 The GARCH Model with Trading Volume
ML Estimates for the 20 Largest Firms

$$R_t = \alpha_0 + \varepsilon_t,$$

$$\varepsilon_t | (I_{t-1}, VOL_t) \sim N(0, h_t^2),$$

$$h_t^2 = \alpha_1 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 h_{t-1}^2 + \alpha_4 VOL_t.$$

This table presents the *ML* estimate of the GARCH(1,1) with trading volume (VOL_t). *ML* is the maximum likelihood function value. *S*, *K* and *J-B* are the skewness, kurtosis and Jarque-Bera statistic for adjusted residuals ε_t/h_t, respectively. The t-ratios are reported in parentheses.

	ε^2_{t-1} (*t-ratio*)	h^2_{t-1} (*t-ratio*)	VOL_t (*t-ratio*)	*ML* *s*	*k*	*J-B*
1	0.263	0.15	0.000094	3031.4		
	(4.09)	(0.99)	(4.53)	0.748	11.96	5041.79
2	0.039	0.156	0.000085	5710.7		
	(1.53)	(2.20)	(4.14)	-.157	28.4	39402.9
3	0.32	0.063	0.000089	4590.4		
	(3.38)	(2.77)	(6.60)	0.359	11.54	4485.28
4	0.125	0.051	0.000087	4247.1		
	(3.29)	(1.46)	(10.97)	0.203	5.25	318.33
5	0.043	0.345	0.000105	5424.3		
	(1.89)	(5.68)	(5.72)	1.016	21.05	20143.5
6	0.068	0.107	0.000111	4310.8		
	(1.22)	(0.61)	(3.83)	-1.54	30.55	46912.2
7	0.315	0.011	0.000118	4176.9		
	(3.40)	(1.04)	(8.77)	0.019	12.12	5071.68
8	0.104	0.04	0.000066	4596.4		
	(3.68)	(1.02)	(10.55)	-.155	6.46	736.69
9	0.068	-.007	0.000087	4117.0		
	(2.90)	(-0.32)	(9.62)	0.243	5.67	448.01
10	0.095	0.006	0.000102	4495.8		
	(3.99)	(0.43)	(7.84)	0.511	7.06	1071.16
11	0.082	-.014	0.000178	2762.4		
	(2.93)	(-0.13)	(6.54)	0.521	5.93	591.68
12	0.079	-.017	0.000074	4350.4		
	(3.22)	(-0.66)	(11.48)	0.31	4.94	253.08
13	0.135	0.076	0.000102	4081.9		
	(3.19)	(1.61)	(7.74)	0.13	8.16	1627.15
14	0.06	0.919	-0.000001	2899.1		
	(1.93)	(25.63)	(-1.08)	0.762	8.12	1742.69
15	0.116	0.026	0.000046	4091.1		
	(3.64)	(0.33)	(10.37)	-.071	4.	62.81
16	0.132	0.009	0.000067	4804.5		
	(5.04)	(0.45)	(7.14)	0.057	7.33	1147.78
17	0.14	0.049	0.000077	4764.6		
	(3.58)	(1.30)	(8.02)	-.265	7.98	1533.39
18	0.135	0.673	0.000062	2959.7		
	(3.70)	(6.50)	(2.16)	0.907	13.32	6696.16
19	0.07	0.03	0.000292	4488.9		
	(3.15)	(1.40)	(7.33)	0.197	12.25	5233.87
20	0.021	-.003	0.000402	3434.6		
	(1.75)	(-0.63)	(7.75)	-.507	12.85	5983.21

Table 2.9 The GARCH(1,1) Model with both the Number of Trades and Trading Volume

$$R_t = \alpha_0 + \varepsilon_t,$$

$$\varepsilon_t | (I_{t-1}, NTS_t, VOL_t) \sim N(0, h_t^2),$$

$$h_t^2 = \alpha_1 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 h_{t-1}^2 + \alpha_4 NTS_t + \alpha_5 VOL_t,$$

where R_t are the residuals from equation 2.11. The mean of estimates for each value weighted portfolio (169 stocks) is reported in Panel A. The number of estimates which are significant at 5% and the number of estimates which are positive are reported in Panel B.

Panel A

Portfolio	$\alpha_0 x10^4$	$\alpha_1 x10^5$	α_2	α_3	$\alpha_4 x10^5$	$\alpha_5 x10^4$	$\alpha_2+\alpha_3$
1 (small)	-6.93	6.2	0.15	0.21	1.9	2.43	0.36
2	-6.99	5.3	0.16	0.29	1.6	1.51	0.45
3	-5.63	3.6	0.14	0.33	1.6	0.54	0.47
4	-3.26	2.2	0.14	0.42	0.8	0.33	0.56
5 (large)	-2.72	0.5	0.14	0.48	0.3	0.11	0.61
All	-5.10	3.6	0.14	0.34	1.2	0.98	0.49

Panel B

	The number of estimates which are significant at 5%						The number of estimates which are positive					
Port-folio	α_0	α_1	α_2	α_3	α_4	α_5	α_0	α_1	α_2	α_3	α_4	α_5
1 (small)	92	139	148	105	94	131	31	157	168	135	108	130
2	88	116	150	118	106	112	33	135	169	124	137	131
3	71	113	155	130	116	87	43	131	169	125	154	105
4	55	90	155	146	106	68	58	106	169	138	158	109
5 (large)	30	90	157	155	92	63	74	82	168	146	154	114
All	336	548	765	654	514	461	239	611	843	668	711	589

Table 2.10 The GARCH(1,1) Model with both the Number of Trades and Trading Volume
ML Estimates for the 20 Largest Firms

$$R_t = \alpha_0 + \varepsilon_t,$$

$$\varepsilon_t | (I_{t-1}, NTS_t, VOL_t) \sim N(0, h_t^2),$$

$$h_t^2 = \alpha_1 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 h_{t-1}^2 + \alpha_4 NTS_t + \alpha_5 VOL_t.$$

This table presents the *ML* estimate of the GARCH(1,1) with the number of trades (NTS_t), and trading volume (VOL_t). *ML* is the maximum likelihood function value. *S*, *K* and *J-B* are the skewness, kurtosis and Jarque-Bera statistic for adjusted residuals ε_t/h_t, respectively. The t-ratios are reported in parentheses.

	ε^2_{t-1}	h^2_{t-1}	NTS_t	VOL_t	*ML*		
	(*t-ratio*)	(*t-ratio*)	(*t-ratio*)	(*t-ratio*)	*s*	*k*	*J-B*
1	0.15	0.6	2.50E-7	2.33E-6	4229.0		
	(4.02)	(5.48)	(1.11)	(0.70)	0.421	5.74	500.02
2	0.15	0.6	1.21E-6	7.66E-6	4407.6		
	(4.87)	(6.30)	(1.22)	(1.89)	0.261	6.54	779.23
3	0.136	0.554	2.07E-6	-1.20E-6	4388.4		
	(3.90)	(6.50)	(4.07)	(-0.42)	0.19	6.21	638.46
4	0.164	-.064	4.21E-7	3.38E-5	3446.2		
	(3.39)	(-1.19)	(2.87)	(7.05)	0.557	5.54	469.48
5	0.15	0.6	9.40E-7	9.83E-8	4218.3		
	(4.49)	(6.48)	(2.43)	(0.03)	0.231	5.6	426.19
6	0.15	0.6	3.90E-8	6.18E-6	3329.7		
	(3.00)	(5.50)	(1.35)	(1.69)	0.316	5.69	467.11
7	0.15	0.6	8.78E-7	-3.78E-6	4267.8		
	(3.98)	(8.02)	(1.69)	(-0.92)	0.266	5.65	445.97
8	0.089	-.027	3.32E-6	9.33E-6	4233.5		
	(3.72)	(-0.31)	(7.86)	(1.10)	0.025	4.27	98.64
9	0.15	0.6	3.47E-7	4.63E-6	4196.4		
	(4.53)	(7.15)	(0.97)	(1.03)	0.227	4.59	167.39
10	0.15	0.6	4.27E-7	4.67E-6	4695.4		
	(4.18)	(6.70)	(1.59)	(1.25)	0.107	5.32	330.42
11	0.15	0.6	-2.04E-7	1.17E-6	4415.1		
	(0.57)	(2.14)	(-0.24)	(0.15)	-.839	17.8	13602.
12	0.15	0.6	2.14E-7	5.68E-6	3963.9		
	(3.32)	(5.60)	(0.77)	(0.49)	0.21	5.83	499.86
13	0.15	0.6	-4.48E-7	1.27E-4	3811.4		
	(2.66)	(4.85)	(-1.02)	(1.25)	-.43	6.9	972.01
14	0.15	0.6	4.88E-7	-4.44E-7	3861.6		
	(4.82)	(6.75)	(1.49)	(-0.15)	0.198	5.33	339.99
15	0.15	0.6	1.12E-7	6.99E-6	4321.1		
	(4.51)	(7.30)	(0.65)	(1.59)	-.027	4.2	88.08
16	0.15	0.6	1.02E-8	2.61E-6	3598.9		
	(1.38)	(1.69)	(0.03)	(0.06)	-.072	7.85	1434.5
17	0.15	0.6	3.29E-7	1.26E-5	3765.5		
	(3.65)	(6.91)	(1.82)	(2.20)	0.29	3.95	75.12
18	0.057	0.088	1.17E-7	2.23E-5	3746.9		
	(2.32)	(1.14)	(1.98)	(5.99)	0.153	3.32	11.88
19	0.15	0.6	-5.57E-8	1.65E-5	3594.2		
	(5.92)	(9.20)	(-1.11)	(3.52)	-.026	4.13	78.74
20	0.15	0.6	-9.38E-8	1.28E-5	3606.6		
	(3.32)	(4.17)	(-1.03)	(0.91)	0.227	5.27	327.89

Table 2.11 The Skewness and Excess Kurtosis of the Standardized Residuals of GARCH Models

The means of skewness and excess kurtosis of the standardized residuals of four GARCH models for each portfolio and all firms are reported.

Portfolio	Skewness			
	GARCH(1,1)	GARCH(1,1) with NTS	GARCH(1,1) with VOL	GARCH(1,1) NTS & VOL
1 (small)	0.82	0.31	0.08	0.16
2	0.81	0.34	0.12	0.28
3	0.69	0.22	0.18	0.29
4	0.64	0.35	0.32	0.47
5 (large)	0.40	0.20	0.16	0.24
All	0.67	0.29	0.17	0.29

Portfolio	Excess Kurtosis			
	GARCH(1,1)	GARCH(1,1) with NTS	GARCH(1,1) with VOL	GARCH(1,1) NTS & VOL
1 (small)	32.90	17.26	18.24	17.80
2	26.72	12.75	15.26	17.58
3	21.78	11.13	12.84	14.33
4	20.75	12.31	12.38	16.35
5 (large)	11.95	7.14	7.81	7.99
All	22.82	12.12	13.31	14.81

2.5 Summary

For most of the stocks in the sample, the GARCH(1,1) fits daily stock returns satisfactorily. Both the number of trades and trading volume can explain a significant part of the conditional variance. Controlling for trading activity reduces the persistence of the conditional variance dramatically. On average, the coefficient of lagged conditional variance decreases by a larger percentage than the coefficient of the square of the past error. However, for most of the firms in the sample, the GARCH effects do not vanish as reported by Lamoureux and Lastrapes (1990). Also, there is still significant kurtosis that is not accounted for in the GARCH process even after controlling for the information flow.

The findings in this chapter effectively relate the conditional volatility with the trading activities, which are used as proxies for the information flow. A significant part of skewness and kurtosis can be captured by the GARCH model. However, the GARCH model can not capture the significant jumps observed in stock prices. In addition, the GARCH model can not investigate the interactions among trading, information and volatility. This is the task of Chapter 3.

CHAPTER 3
INFORMATION, TRADING AND STOCK RETURN VOLATILITY: A MIXED-JUMP-DIFFUSION MODEL

3.1 Introduction

Several studies have analyzed the relative contribution of trading and public information in determining daily stock return volatility. French and Roll (1986), and Barclay, Litzenberger and Warner (1990) use variance estimates around weekends, and during days on which the exchange is closed but businesses are open to analyze the effects of trading and public information on stock price movements. Other studies have analyzed the variance around days on which the exchanges are open, but investors endogenously choose not to trade (Jones, Kaul and Lipson, 1994a). However, the previous studies estimate only the information that is produced during non-trading periods when the exchanges are closed, or when investors endogenously choose not to trade (Jones, Kaul and Lipson, 1994a). Therefore, these estimates do not include public information that is released to the market during normal trading days and when investors endogenously choose to trade. In these circumstances, to infer the relative contribution of private versus public information, one has to make assumptions regarding the flow of public/private information during trading days which can potentially have both public and private information. Jones, Kaul and Lipson (1994a) consider two possible scenarios to assess the relative importance of public and private information in determining

daily stock return volatility. Under the first scenario it is assumed that public information flow during trading days is the same as that during non-trading days, and that trading is necessary for private information to influence prices. Under this scenario, the ratio of non-trading to trading day volatility will measure the relative importance of public versus private information in determining stock return volatility. Alternatively, if private information is a negligible component of the flow of information, and public information leads to trading, then the ratio of non-trading to trading day volatility will measure the relative importance of public information during non-trading and trading periods. Jones, Kaul and Lipson (1994a) find that for Nasdaq-NMS stocks over the 1984-1991 period the ratio of non-trading to trading volatility is between .20 and .30. It means that a substantial fraction of the daily volatility is generated with no trading.

In this chapter I employ a different methodology that is based on the mixed jump-diffusion model to *separately* estimate the relative importance of private information, public information, noise and trading activity in determining daily stock return volatility. Unlike the methodology employed by Jones, Kaul and Lipson (1994a) in which the effect of non-trading is estimated using days on which investors endogenously choose not to trade, in our methodology I condition the diffusion and the jump model parameters (variance parameters) on proxies for trading activity (number of trades and turnover

volume) to infer the relative contributions of non-trading and trading to the diffusion and the jump processes.

I assume that the daily stock return process consists of a diffusion process and an independent compound event process. The diffusion process captures small movements in stock prices due to strategic trading by informed agents (see for example the model by Kyle, 1985), and the effects of noise traders (liquidity traders and uninformed traders), and market imperfections (microstructure biases such as price discreteness). The compound event process models the discrete jumps in prices due to significant unanticipated public information flows that are associated with trading as well as non trading. Innovations in public information are posited to arrive according to a Poisson process. The resulting model is the mixed jump-diffusion model.

Several studies analyze the informational role of prices and the trading strategies of privately informed agents (for a detailed review see Admati and Pfleiderer, 1988). Kyle (1985) argues that if information is long lived, then informed agents will trade strategically, releasing information gradually to the market. Under this scenario one would expect most of the volatility to be due to trading, the price change would be smooth and be best described by a diffusion process. On the other hand, if there is very little information based trading, or if information is short lived, then one would expect information to be released to the market in discrete packets, causing stock prices to jump. Also, under this scenario the

diffusion process will be mainly driven by noise. These models suggest that the stochastic behavior of the price process can not be separated from the process by which information is acquired and disseminated either through trading or through public release. Further, the dichotomy between public (discrete) versus private(smooth) information suggests that the mixed jump-diffusion model is a natural and intuitive way to separate the effects of private (strategic trading) information and noise from the effects of public information. The basic model I employ is the mixed jump-diffusion model originally proposed by Press (1967) to describe daily stock returns.

In addition, I also examine the effects of trading on the diffusion process as well as on the jump process by conditioning the parameters of the jump-diffusion model on proxies for trading activity. If we assume that trading is necessary for private information to influence prices, then the components of the diffusion and jump process variances that are related to trading will reflect the impact of private information on volatility. Alternatively, if private information is a small fraction of the total information flow, then the components of the volatility associated with trading will reflect the effects of noise or differences in opinions. I employ the number of transactions as a conditioning variable in the diffusion process variance and in the jump process (Poisson parameter) to separate the diffusion and jump volatility into trading and non-trading related components. Trading volume is also used. Since the results are very similar, they are not reported.

In addition to providing an intuitive way to separate the volatility into different components, the mixed jump-diffusion model is statistically superior to a pure diffusion model in describing daily stock return data. Nimalendran (1994) finds that the mixed jump-diffusion model is statistically superior to the pure diffusion model in nearly 90 percent of the firms studied. Further, Brauer (1986) finds that parameter estimates of the mixed jump-diffusion model are good proxies for information surprises, and the estimate of the Poisson parameter captures the frequency of the surprises. Also, Akgiray and Booth (1987), Ball and Torous (1985), Jarrow and Rosenfeld (1984), find that the mixed jump-diffusion model captures the observed skewness and kurtosis in daily returns and is superior to the pure diffusion model in describing the dynamics of daily stock returns.

I use the same sample of 845 firms traded on the Nasdaq-NMS over the 1986-1991 period as used in chapter 2 to analyze the relative effects of private versus public information on daily stock return volatility. First, we document that for all firms in our sample the jump-diffusion model is statistically superior to the pure diffusion model in describing daily continuously compounded returns based on the average of the closing bid and ask prices. As discussed in Chapter 2, this eliminates any potential biases due to bid-ask bounce. I also partition the firms into five portfolios based on market capitalization as in Chapter 2, and I estimate the relative volatility associated with the diffusion and the jump process

parameters. For the smallest market capitalization portfolio, on average less than 3.5 percent of the total volatility is contributed by the diffusion process, while for the largest capitalization firms about 32 percent of the total volatility comes from the diffusion process. The fraction of the volatility due to diffusion is monatonically increasing with market value.

I decompose the volatility into: non-trading related diffusion component, a trading related diffusion component, a non-trading related jump component and a trading related jump component using a conditional jump-diffusion model. The trade related diffusion variance varies from 0.0274 percent for small firms to 27.8 percent for large firms. If we believe that the trading related diffusion variance measures the relative importance of strategic trading by informed agents, then private information has no impact on small market value firms and accounts for 27.8% of the total volatility for the large firms. Alternatively, if the diffusion process is entirely driven by noise trading, then for small firms the effect of noise is negligible while for large firms it accounts for 27.8 percent of the volatility. The component of the diffusion variance that is not related to trading varies from 3.43 percent to 7.55 percent. This could be due to minor public information and/or market imperfections.

The analysis of the jump process reveals that discrete price changes related to trading generate from 68 percent to 81% of the volatility, while the non-trade related discrete price changes monatonically decrease from 27.4 percent for small firms

to 0.0189 percent for the large firms. This analysis and the data indicate that for large firms in the Nasdaq-NMS system, approximately 96 percent of the volatility in prices is related to private and public information when investors endogenously choose to trade. For the smallest market value firms, however, only 69.1 percent of the volatility is generated on days when investors endogenously choose to trade.

Jones, Kaul and Lipson (1994a) report that between 20 percent (small firms) and 30 percent (large firms) of the price movements occur on days when there is no trading, but the exchanges and businesses are open. Our results indicate that for small market capitalization firms 30.8 percent of the volatility generated is not related to trading, while for large firms only 4.29 percent of the volatility is generated when there is no trading.

To distinguish the sources (information versus noise) that generate volatility, I examine the cross sectional relationship between the adverse selection component of the bid-ask spread and the various components of volatility. I estimate the adverse selection component using the approach in George, Kaul and Nimalendran (1991). To avoid any spurious correlation due to estimation errors of the adverse selection component and the parameters of the jump-diffusion model, I estimate the parameters of the mixed jump-diffusion model during the period 1986-1991, while the spread and the adverse selection component of the spread are estimated in the period 01/03/92-12/31/92. I find that the adverse selection component is positively related

to the jump process volatility that is not related to trading. The trading related component of the jump process has no explanatory power. On the other hand, both components of the diffusion volatility are negatively related to the adverse selection component of the spread. If the adverse selection component of the spread is driven by information asymmetry (for example, the model by Glosten and Milgrom, 1985) then the analysis suggests that the information asymmetry is positively related to discrete jumps in prices that are not associated with trading. More importantly, the negative relationship between trade induced volatility and the adverse selection component of the spread supports the hypothesis that trading is dominated by noise traders as opposed to informed traders.

This chapter is organized as follows. In section 3.2 I describe the unconditional jump-diffusion model and the estimation procedure. The sample data is described in Section 3.3. The conditional jump-diffusion model as well as the results are analyzed in Section 3.4. In section 3.5, I compare alternative models for the stock return dynamics. Section 3.6 concludes the chapter.

3.2 Methodology

This section briefly presents the stochastic process under investigation and the procedure to estimate the parameter of the model.

3.2.1 The Mixed Jump-Diffusion Model

The mixed jump-diffusion model of security returns was first introduced by Press (1967). Essentially, Press models the price of a security as the sum of a continuous, nonstationary process (geometric Brownian motion), which may represent temporary imbalances between supply and demand, and a jump process, which captures the arrivals of unanticipated information. This model can explain the excess skewness and kurtosis better than a normal distribution.

Specifically, Press suggests that after considering the discontinuities of the price of a security, the process could be described by a Wiener diffusion process augmented by a compound Poisson process:

$$\frac{dS_t}{S_t} = \alpha\,dt + \sigma\,dz_t + dq_t, \quad \text{and } dq_t = \sum_{j=1}^{q_t} Y_j, \tag{3.1}$$

where S_t is the price of the stock, α is the drift of the diffusion process, σ^2 is the instantaneous variance of the diffusion process, z_t is a Wiener process, and q_t is a Poisson counting process with intensity parameter λ_t. The jump amplitudes, Y_j, are independent and identically distributed log normal random variables with mean μ and variance δ^2. All the random variables are assumed to be mutually independent. The unconditional mean and variance of the returns are $(\alpha-\sigma^2/2+\lambda\mu)$ and $[\sigma^2 + \lambda(\mu^2 + \delta^2)]$ respectively. Further, the density is leptokurtic for $\lambda > 0$, and skewed when μ is not equal to zero.

The skewness and kurtosis are given by $[\lambda\mu(\mu^2+3\delta^2)]/[\sigma^2+\lambda(\mu^2+\delta^2)]^{3/2}$ and $[\lambda(\mu^4+6\mu^2\delta^2+3\delta^4)]/[\sigma^2+\lambda(\mu^2+\delta^2)]^2$, respectively.

We assume that the compound Poisson process represents the price changes due to the release of unanticipated public information. These information events are posited to arrive according to a Poisson process and the effect of each event on stock price is assumed to be distributed randomly. The mean number of such information event is λ. In addition to the discrete effect due to the information, it is also assumed that the effect of trading can be represented by the independent diffusion process.

3.2.2 Estimation

The parameters of the compound events model are estimated via maximum likelihood technique. Let x_t be the logarithm of price relative, $\ln(\frac{S_t}{S_{t-1}})$, at time t, and $W = (w_t, t=1,\ldots,T)$ be the daily continuously compounded security returns in the estimation period. If $\theta = (\alpha, \sigma^2, \mu, \delta^2, \lambda)$ denotes the parameters of the mixed jump-diffusion model described in Equation 1, then the unconditional density of daily returns is

$$f(x_t) = \sum_{j=0}^{\infty} \frac{1}{[2\pi(\sigma^2 + \delta^2 j)]^{1/2}} \exp\left(\frac{(x_t - \alpha + \sigma^2/2 - \mu j)^2}{2(\sigma^2 + \delta^2 j)}\right) \frac{e^{-\lambda}\lambda^j}{j!} \quad (3.2)$$

If we assume that the daily returns are independent and identically distributed, then the logarithm of the likelihood function for T return realizations is

$$L = \ln l(\theta, W) = -T\lambda - \frac{T}{2}\ln(2\pi) + \sum_{t=1}^{T} \ln(Z_t),$$

$$\text{where } Z_t = \sum_{j=0}^{\infty} \frac{1}{(\sigma^2 + \delta^2 j)^{1/2}} \exp\left[-\frac{(w_t - \alpha + \frac{\sigma^2}{2} - \mu j)^2}{2(\sigma^2 + \delta^2 j)}\right] \frac{\lambda^j}{j!} \quad (3.3)$$

As usual, necessary conditions for the existence of *MLE*'s for θ are provided by setting the first partial derivatives of the likelihood function with respect to the parameters equal to zero. The corresponding sufficient conditions require that the matrix of second partial derivatives evaluated at the optimum is negative semi-definite. Subject to regularity conditions, the inverse of the information matrix evaluated at the optimum gives an estimate for the asymptotic variance-covariance matrix of the estimators, and the *MLE*'s are asymptotically normal. Hence, the maximum likelihood method allows us to construct approximate confidence intervals for the parameter estimators of interest, which are asymptotically efficient. The equations obtained from the first order conditions are nonlinear in the parameters, and an analytic solution does not exist. Hence, a numerical technique (the quadratic hill-climbing algorithm proposed by Goldfeld, Quandt and Trotter, 1966) is employed to find the estimates that maximize the likelihood function. The computation is done by using IMSL math library and GQOPT numerical optimizing package written in FORTRAN.

3.3 Data

The estimation of the mixed jump-diffusion model parameters are based on the same returns as the ones used for the GARCH models of Chapter 2, which are calculated by using the average of the bid and ask quotes at the end of the day. The choice of the returns based on the average of bid and ask for the mixed jump-diffusion model is more important than the GARCH models. Particularly, for small capitalization firms, the bounce between bid and ask prices could mimic discrete jumps. This would lead to spurious estimates for the jump process parameters.

As in Chapter 2, to control for the stickiness and lagged adjustment of prices we follow the same procedure employed by Jones, Kaul and Lipson (1994a). First, estimate the following model.

$$R'_{it} = \sum_{k=1}^{5} \alpha_{ik} D_{kt} + \sum_{j=0}^{5} \beta_{ij} R_{m(t-j)} + \sum_{l=1}^{5} \gamma_{il} R'_{i(t-l)} + R_{it}, \quad (3.4)$$

where R'_{it} is the return based on the average of the bid-ask prices on stock 'i' at time 't', R_{mt} is the return on the value weighted market portfolio, D_{kt} is a dummy variable for the day of the week k. All the maximum likelihood estimates are based on the error term, adjusted returns $R_{i,t}$.

In Table 3.1 we report some summary statistics for the overall sample and for the sub-samples based on the market value of the firms. The market value of the firms is calculated as the average of the market values at the beginning of the sample

period and at the end of the period. Similarly the number of shares outstanding is also based on the average of the beginning and the end values. All the other variables reported are the averages based on all the daily observations during the period from March 3, 1986 to December 31, 1991.

The descriptive statistics reported in Table 3.1 provide an indication of the wide variation in the characteristics of the securities in the sample. The average market value varies from 14 million dollars for the smallest portfolio to 723 million dollars for the largest. The ratio of bid-ask spread to price varies from 1.70 percent to 9.39 percent. These numbers are very similar to the those reported by Jones, Kaul and Lipson (1994b). The minor differences may be attributable to the way I calculate market value which is based on the average of the beginning and end of the sample period, while Jones, Kaul and Lipson (1994a) use the mid point of the sample period span. Also we have 845 securities as opposed to the 825 reported by Jones, Kaul and Lipson (1994a). Further, Jones, Kaul and Lipson (1994a) require that data be available for all the trading and that every statistic (except volume) that is reported have a monatomic relationship with market value. This also justifies the use of market value to form portfolios. The firms in this sample have market values that are much lower than the average market value in the NYSE/AMEX firms. Further, the average ratio of bid-ask spread to price of 4.95 percent is significantly higher than the average spread ratio in the NYSE/AMEX which is equal to 2.82% at the end of 1988 (see Kim, 1988). The

difference in market value and spreads are mainly due to the top 25% of the firms whose spreads are typically less than 1%. Therefore, this sample is more representative of the lower 75% of the firms in market value traded in the NYSE/AMEX system. Clearly, in our analysis, the trading mechanism also could be significant in determining how information is disseminated and incorporated into prices. Therefore, we have to be cautious about drawing inferences regarding NYSE/AMEX firms based on the Nasdaq-NMS firms.

3.4 Results

3.4.1 The Mixed Jump-Diffusion Model

First, we estimate the mixed jump-diffusion model which consists of a geometric Brownian motion augmented by an independent compound Poisson process with log-normally distributed jump amplitudes. If S_t is the price of the stock at time t, and $w_t = \ln(S_t/S_{t-1})$ is the continuously compounded return, the *discrete* time version of the model is

$$w_t = (\alpha - \frac{\sigma^2}{2}) + \sigma Z_t + \sum_{i=1}^{q_t} \ln Y_i, \qquad (3.5)$$

where

Z_t =a standard Wiener process with instantaneous mean and variance per unit time of α and σ^2 ,

Table 3.1 Descriptive Statistics of Nasdaq-NMS stocks
3/3/1986-12/31/1991

This table contains market value (average of the market values on March 3, 1986 and December, 31, 1991), the average of the closing bid and ask prices, the average volume turnover (the daily volume divided by the number of shares outstanding for each day), the average number of transactions, and the average proportional spread ([ask-bid]/(0.5[ask+bid])). The data is reported for all stocks, and for five portfolios based on market value of equity.

Portfolio	No. of Firms	Market Value in 10^6	Average of the Bid-Ask Price ($)	Volume Turn-Over x10^3	No. of Transac-tions	Avg.Tran-saction Size in 1000 shares	Proportional Spread (%)
1(small)	169	14.28	6.59	1.93	4.18	1396	9.39
2	169	33.96	10.45	3.17	9.01	1496	5.90
3	169	65.48	13.64	3.07	12.87	1652	4.63
4	169	154.9	22.59	3.21	18.4	1619	3.16
5(large)	169	723.4	28.92	3.81	62.4	1776	1.70
All	845	198.6	16.45	3.04	21.4	1588	4.95

Table 3.2 Summary Statistics for Excess Kurtosis:

In this table we report the median, minimum and maximum of the excess kurtosis for each portfolio of firms for all the firms for the adjusted stock returns R_i. NTS_i is the number of transactions. (The mean is reported in Table 2.1)

Portfolio	R_i			$R_i/NTS_i^{0.5}$		
	median	min.	max.	median	min.	max.
1 (small)	19.50	1.91	247.96	8.26	0.16	135.00
2	16.34	-0.81	318.00	3.83	-1.60	115.75
3	12.64	0.20	194.75	2.85	-1.89	350.52
4	9.46	0.65	509.12	1.21	-2.38	870.49
5 (large)	4.45	-1.69	71.56	-1.00	-2.83	32.11
All	11.89	-1.69	509.12	2.57	-2.83	870.49

q_t = a Poisson process with parameter λ, and

lnY_i = one member of family of independent and identically normally distributed random variables with mean μ and variance δ^2 per unit time, which are also independent of q_t.

In the above model for stock returns, we assume that impacts due to strategic trading, noise trading, and microstructure biases cause stock prices to fluctuate randomly, and this is modeled by a Wiener (diffusion) process. In addition, we assume that over the interval $(t-1)$ to t, public information that has a significant effect on stock price arrives according to a Poisson process q_t, and each Poisson information event causes a discrete jump in stock price of size Y_i, $i=1, 2, \ldots, q_t$. The jumps are assumed to be independent and log normally distributed random variables. This results in the compound Poisson process $\{G_t, t > 0\}$, where

$$G_t = \sum_{i=1}^{q_t} \ln(Y_i). \qquad (3.6)$$

The mean and variance of the above process per unit time are $\lambda\mu$ and $\lambda[\mu^2+\delta^2]$, respectively. The mean and variance of the joint process w_t are $(\alpha-\sigma^2/2+\lambda\mu)$ and $\Sigma^2 = [\sigma^2 + \lambda(\mu^2 + \delta^2)]$, respectively, over one unit time.

In our stochastic model we assume that the diffusion process models the effects due to liquidity, noise and insiders' trading, while the compound event process models the effects of

public information. Therefore, estimates of the diffusion variance σ^2 will be a good proxy for the volatility due to liquidity and insiders' trading, while estimates of λ and δ^2 provide proxies for the frequency of public information arrival and the volatility associated with it.

One of the main advantages of the jump-diffusion model over a pure diffusion model in describing stock return dynamics is its ability to model the observed skewness and kurtosis in stock returns. Heteroskedasticity in stock returns is one possible source of the kurtosis, and traditionally GARCH type of models have been employed to capture this. However, GARCH models do not completely eliminate the excess kurtosis. Our sample of Nasdaq-NMS firms consists of many small market value, low priced stocks. These stocks are likely to exhibit more kurtosis than larger stocks such as the DJ 30 stocks. In Table 3.2 we summarize the excess kurtosis for our sample partitioned into five portfolios. In addition to the excess kurtosis for the adjusted returns R_i, we also calculate the excess kurtosis for stock returns divided by the square root of the number of transactions. This is consistent with the mixture of distributions hypothesis (MDH) proposed by Clark (1973), Westerfield (1977), Tauchen and Pitts (1983), Harris (1987), and Lamoureux and Lastrapes (1990). This MDH asserts that the stock returns follow a subordinated process, in which the number of trades (or trading volume) proxies for the directing process, for information arrival. Therefore, under a pure diffusion model the variance of stock returns is proportional to the number of

trades. The stock returns can be made homoskedastic by dividing the returns by the square root of the number of trades.

From Table 3.2, we note that in every portfolio there is significant excess kurtosis for individual stocks. Not surprisingly, the average excess kurtosis is monatonically decreasing with increasing firm size. More importantly, dividing by the number of trades does not eliminate the excess kurtosis. The average excess kurtosis is lower for the transformed series.

However, even for the largest market value firms, it is equal to 3.5 (s.e. = 0.128). This suggests that a pure diffusion model will not adequately capture the excess kurtosis even if the variance is conditioned on the number of transactions.

We estimate the parameters for the 845 firms over the period 1986-1991 (1464 observations) by numerically optimizing the log-likelihood function $L(\theta; W)$ with respect to the parameter vector $\theta = (\alpha, \sigma^2, \mu, \delta^2, \lambda)$, for a given set of continuously compounded daily returns W. Maximum likelihood estimators have several desirable properties. The estimators are consistent, invariant to transformations, and asymptotically normal. Further, through the Hessian matrix, we can obtain standard errors for the estimates. In addition, maximum likelihood technique permits statistical tests of alternative models for stock returns. Since the pure diffusion model is nested within the jump-diffusion model, we can use the likelihood ratio test to compare the two models statistically. Specifically, if $L(\theta_1; W)$ is the maximized log-likelihood function under the pure

diffusion model (null) and $L(\theta_J^*; W)$ is the maximized log-likelihood function under the jump-diffusion model, then the statistic Λ described in Equation (3.7) is asymptotically distributed chi-squared with three (the number of imposed restrictions) degrees of freedom:

$$\Lambda = 2\left[L(\theta_D^*; W) - L(\theta_J^*; W)\right] \sim \chi^2(3). \qquad (3.7)$$

In Table 3.3 we report the summary statistics for the parameter estimates. The statistics reported are the medians based on the firms in each portfolio and for all the firms. The reported standard errors of medians for each group are calculated with a bootstrap technique.

In Table 3.3, the results based on the jump-diffusion model estimates indicate that the trade related volatility which is approximated by the diffusion process variance σ^2 is increasing with firm size. This is consistent with the increase in number of trades with firm size that is reported in Table 3.1. More importantly, the jump variance decreases monatonically from average of 9.34×10^{-4} for the smallest market value firms to 3.72×10^{-4} for the largest market value firms. I also observe a similar monatomic decrease for the total variance of the jump component which decreases from 4.16×10^{-4} for the smallest firms to 1.73×10^{-4} for the largest firms. These results are consistent with the notion that large firms are generally followed by many investors and analysts. Therefore, for these firms the public information will be less of a surprise and would lead to smaller

volatility. While small firms are likely to be followed by fewer investors and analysts. For these firms information releases will have a significant effect on prices. However, the significant jumps exist for all size of firms as evidenced by the statistically significant λ at any conventional level. Finally, in the last column of Table 3.3 I report the average ratio of the diffusion volatility to total volatility. Following scenario 1 in Jones, Kaul and Lipson (1994a), this provides a measure of the total volatility that is due to trading. For the smallest market value firms, the fraction of volatility due to trading is 0.033, while for the largest market value firms the fraction is 0.20. However, this model can not shed more light regarding the information processing of financial markets without making very strong assumptions. Therefore, in the next section I directly investigate the impacts of both private and public information on the price changes through trading using and conditional mixed jump-diffusion model.

3.4.2 Effects of Trading on Diffusion and Jump Process

We find that between 80% and 97% of the volatility is due to discrete price changes or public information. In addition, a non-trivial fraction of the public information may be unrelated to trading activity. Therefore, in this section I estimate a conditional jump-diffusion model in which the diffusion volatility and the frequency of information arrivals are conditioned on the number of transaction and trading volume.

Table 3.3 ML Parameter Estimates for
the Mixed Jump-Diffusion Model

In this table we summarize the estimates based on the mixed jump-diffusion model described by the following equation:

$$R_{i,t} = (\alpha - \frac{\sigma_i^2}{2}) + \sigma_i Z_t + \sum_{j=1}^{q_t} \ln Y_j,$$

The jump-diffusion model was estimated for each of the 845 firms. The estimates are based on all the valid observations during the period March 3, 1986 through December 31, 1991, except for the period October 15, 1987 through October 31, 1987. We remove these observations to mitigate the effects due to the crash which can unduly influence the volatility. There were 1464 trading days in this period. The values reported are the median values based on individual stock estimates for each group of firms. The standard errors of the median [s.e] calculated by using bootstrap technique is given within parentheses (.). The instantaneous mean and variance per unit time of the diffusion process is given by α and σ^2. The Poisson parameter λ measures the frequency of public information. The mean and variance of each event is described by μ and δ^2. The variance of the compound event process is $\Delta^2 = \lambda[\mu^2+\delta^2]$. The variance of the joint process $\Sigma^2 = [\sigma^2 + \lambda(\mu^2 + \delta^2)]$. Finally, the last column gives the fraction of the total volatility due to trading, $\tau = \sigma^2/\Sigma^2$.

	Diffusion		Jump process x 10^4				Total	
Portfolio	α	$\sigma^2 \times 10^4$	μ	λ	δ^2	Δ^2	Σ^2	$\tau = \sigma^2/\Sigma^2$
1 (small)	-0.0284	0.163	0.0139	0.439	9.34	4.16	4.44	0.0334
	(0.00592)	(0.0287)	(0.0107)	(0.0266)	(0.913)	(0.445)	(0.413)	(0.00267)
2	-0.0801	0.389	0.115	0.467	8.82	4.21	4.74	0.0796
	(0.00872)	(0.0403)	(0.0143)	(0.0241)	(0.9)	(0.361)	(0.389)	(0.00619)
3	-0.0729	0.387	0.127	0.443	6.92	3.32	3.87	0.112
	(0.0112)	(0.0581)	(0.0138)	(0.0266)	(0.684)	(0.279)	(0.307)	(0.00848)
4	-0.0772	0.372	0.161	0.417	5.32	2.16	2.51	0.151
	(0.00536)	(0.0444)	(0.0168)	(0.0237)	(0.481)	(0.182)	(0.267)	(0.0101)
5 (large)	-0.0813	0.459	0.138	0.457	3.72	1.73	2.32	0.201
	(0.00605)	(0.0457)	(0.00954)	(0.0239)	(0.376)	(0.112)	(0.139)	(0.0124)
All	-0.0709	0.359	0.119	0.446	6.6	2.9	3.39	0.115
	(0.00406)	(0.0224)	(0.00795)	(0.0211)	(0.357)	(0.169)	(0.225)	(0.00678)

This allows us to separate the two sources of volatility further into one component that is related to trading, and the other component that is generated during non-trading intervals.

Specifically, in the conditional mixed jump-diffusion model I augment the unconditional version of the mixed jump-diffusion model described by equation (3.1) by conditioning both the diffusion variance and the Poisson parameter, on trade related variables. In particular, I employ number of transactions or trading volume as the conditioning variable. These variables are also employed by Jones, Kaul and Lipson (1994b). The conditional diffusion variance for firm *i* and time *t* is, σ_{it}^2, and the conditional frequency of jumps for firm *i* and day *t*, λ_{it} , are given by the following equations.

$$\begin{aligned} \sigma_{it}^2 &= \sigma_{i0}^2 + \sigma_{i1}^2(Xit) \\ \lambda_{it} &= \lambda_{i0} + \lambda_{i1}(Xit) \end{aligned} \tag{3.8}$$

where X_{it} is the number of transactions NTS_{it} or trading volume VOL_{it} for firm '*i*' on day '*t*'. The discrete time version of the model is with subscript '*i*' suppressed for clarity is,

$$w_t|x_t = (\alpha - \frac{\sigma_t^2}{2}) + \sigma_t Z_t + \sum_{j=1}^{q_t} \ln Y_j, \tag{3.9}$$

where

w_t = the adjusted continuously compounded stock returns,

Z_t = a standard Wiener process with instantaneous mean and variance per unit time of μ ,and σ_t^2,

q_t = a Poisson process with parameter λ_t , and

lnY_j = one member of family of independent and identically normally distributed random variables.

Again, this model is estimated using the maximum likelihood technique described in section 3.2.2.

Since the empirical results based on the number of transactions and trading volume are not significantly different, only the estimates using the number of transactions are reported. In Table 3.4 I present the median estimates of the volatility parameters for the five portfolios. First, I document that number of trades significantly explains the volatility in the diffusion process for all the stocks. More importantly, the frequency of public information per unit time, that is not related to trading which is approximated by λ_0 generally decreases with increasing firm's market value. Similarly, the effect of trading on discrete price changes which is approximated by λ_1 monatonically decreases with firm's market value. However the frequency of information events which is measured by $\lambda_0 + \lambda_1 E(x_t)$ monatonically increases with firm's market value. $E(x_t)$ is the expected value of number of trades. This suggests that the information events for large firms are generated at a relatively higher frequency. Finally, the volatility of price changes conditional on a jump decreases monatonically from 6.85×10^{-4} for the smallest firms to 2.23×10^{-4} for the largest market value portfolio of firms. The results are consistent with the pattern that for large firms information is

released to the market in small quantities and each trade conveys less information than for smaller firms.

One of the benefits of the jump-diffusion model over traditional models such as the GARCH models or the model employed by Jones, Kaul and Lipson (1994b), is that it allows one to estimate continuous fluctuations in stock prices as well as discrete price changes. The GARCH framework allows a stochastic process to condition the volatility on variables such as number of transactions or trading volume. However, the GARCH framework does not provide an intuitively appealing way to separate the volatility into a trading and non-trading components associated with public and private information. Jones, Kaul and Lipson (1994b) use price changes around non-trading days to estimate the volatility over non-trading periods. The Jones, Kaul and Lipson (1994b) methodology provides important information regarding how information is incorporated into prices. However, their non-trading volatility does not capture all the public information that is released to the market. The conditional jump-diffusion model provides a measure of both the public information on non-trading periods as well as the public information that is released on trading periods. I can separately estimate the following four components using the conditional jump-diffusion model:

σ_{i0}^2= Non-trading component of diffusion volatility for firm i,

$\sigma_{i1}^2 * E(X_t)$ =Trading related diffusion volatility for firm i,

$\Delta_{i0}^2 = \lambda_{i0} (\delta_i^2 + \mu_i^2)$ Non-trading component of jump volatility for

firm i,

$\Delta_{i1}^2 = (\lambda_{i1} * E(X_i))(\delta_i^2 + \mu_i^2)$ = Trading related jump volatility for firm i.

In Table 3.5 I report the fraction (as a percentage) of the total volatility that is attributable to different sources for each of the five portfolios as well as for all the firms. In particular, I decompose the diffusion volatility and the jump-process volatility into trading and non-trading components. The trading related diffusion variance measures the relative importance of strategic trading by informed agents and/or volatility induced by trading noise. I would also expect that for large firms with many trades, the informed agents should be able to trade more aggressively without significantly revealing their identity. This means a large component of the information will be gradually incorporated into prices. What we document is consistent with this story. Specifically, the trade related component of the diffusion variance is increasing monatonically with market value. For the smallest market value portfolio, less than one percent is due to trading, while for the largest market value portfolio nearly 28 percent is related to trading. However, the positive relationship between trading related diffusion volatility and the firm size can be explained by both more private information events and more liquidity traders for large firms. The results in Table 3.5 also show the dramatic difference in the variance due to public information during trading and non-trading periods. For the smallest market value

firms approximately 27 percent of the variance is due to discrete changes during non-trading periods, and 69 percent is due to discrete changes associated with trading. In the case of the largest market value portfolio, the variance in the non-trading periods is less than one percent compared to 68 percent due to trading. However, the trading related volatility in jump process does not vary monatonically with firm's size. But the ratio of trading to non-trading volatility in jump process remains positively related to firm size. In addition, for large firms on the Nasdaq-NMS system, approximately 96 percent of the total volatility in prices is related to trading, while for the smallest market value firms only 69 percent of the volatility is generated through trading.

3.4.3 Sources of Stock Return Volatility: Private Information, Public Information and Noise

In this section we examine the sources that generate the different components of the volatility by examining the effect of the different components of volatility on market microstructure. I follow Jones, Kaul and Lipson (1994a) and examine two polar scenarios. First, I assume that the effect of public information is captured by the compound event process, while private information is incorporated into prices through trading. In particular, if informed traders trade strategically, then the component of the diffusion volatility associated with trading will reflect private information. Under this scenario we would expect the trading related diffusion volatility to be

Table 3.4 Summary Statistics of Estimates Based on the Conditional Mixed Jump-Diffusion Model

In this table we report the summary statistics for the parameter estimates based on the conditional mixed jump-diffusion model with the number of transactions as the conditioning variable. The conditional diffusion variance, σ_t^2, and the conditional frequency of jumps, λ_t, are given by the following equations: $\sigma_t^2 = \sigma_0^2+\sigma_1^2 X_t$, $\lambda_t = \lambda_0+\lambda_1 X_t$, where X_t is the number of trades NTS$_t$. The discrete time version of the model is

$$R_{i,t}|X = (\alpha - \frac{\sigma_i^2}{2}) + \sigma_i Z_t + \sum_{j=1}^{q_t} \ln Y_j,$$

The values reported are the median values based on individual stock estimates for each group of firms. The standard errors of the median [s.e] calculated with bootstrap technique is given within parentheses.

Portfolio	Diffusion Process		Jump Process		
	$\sigma_0^2 \times 10^4$	$\sigma_1^2 \times 10^4$	λ_0	λ_1	$\delta^2 \times 10^4$
1 (small)	0.151	0.000366	0.145	0.138	6.85
	(0.0204)	(0.000378)	(0.00952)	(0.00955)	(0.636)
2	0.266	0.0224	0.0867	0.0694	6.85
	(0.0269)	(0.00548)	(0.0105)	(0.00792)	(0.625)
3	0.231	0.0231	0.0528	0.0565	5.3
	(0.025)	(0.00398)	(0.00831)	(0.00665)	(0.572)
4	0.165	0.0196	0.016	0.0474	3.62
	(0.0159)	(0.00177)	(0.00513)	(0.00448)	(0.296)
5 (large)	0.0765	0.0173	0.000177	0.0203	2.23
	(0.00749)	(0.00184)	(0.000111)	(0.00192)	(0.216)
All	0.173	0.0161	0.0524	0.0576	4.6
	(0.0107)	(0.00129)	(0.00685)	(0.00379)	(0.259)

Table 3.5 Diffusion Versus Jump Volatility and the Effects of Trade

In this table we present the different sources of daily stock return volatility. Specifically, we use the estimates from the conditional jump-diffusion model for each firm to separately estimate the diffusion and jump components of the volatility that are associated with trading and that which is generated during non-trading periods. The conditioning variable employed is the number of transactions each day. We report the median percentages of the total volatility which are due to different sources. The standard errors [s.e] of the median estimates are given in the parentheses, and are calculated by using bootstrap technique based upon the sample estimates for each portfolio of firms.

Conditional Mixed Jump-Diffusion Model:

$$\sigma_t^2 = \sigma_0^2 + \sigma_1^2 X_t,$$
$$\lambda_t = \lambda_0 + \lambda_1 X_t,$$

where, X_t is the number of trades $NTSt$. $\Sigma^2 = \sigma^2 + \lambda(\delta^2 + \mu^2)$.

	Diffusion Process (x100)		Jump Process (x100)	
Portfolio	Non-Trading σ_0^2/Σ^2	Trading $\sigma_1^2 \times E(X)/\Sigma^2$	Non-Trading $\Delta_0^2/\Sigma^2 =$ $\lambda_0(\delta^2+\mu^2)/\Sigma^2$	Trading $\Delta_1^2/\Sigma^2 =$ $(\lambda_1 * E(X))(\delta^2+\mu^2)/\Sigma^2$
1 (small)	3.4	0.0274	27.4	69.1
	(0.27)	(0.02)	(2.04)	(3.16)
2	5.72	2.46	13.9	77.9
	(0.57)	(0.636)	(1.84)	(3.41)
3	6.85	6.51	7.58	79.0
	(0.427)	(1.39)	(1.55)	(3.26)
4	7.55	9.24	2.27	81.0
	(0.53)	(1.23)	(0.97)	(3.4)
5 (large)	4.27	27.8	0.0189	68.0
	(0.45)	(3.02)	(0.01)	(3.46)
All	5.62	6.04	7.69	80.1
	(0.33)	(0.56)	(0.99)	(3.2)

positively related to information asymmetry. Therefore this volatility should be positively related to the adverse selection component of the spread (Glosten and Milgrom, 1985). Alternatively, if trading is dominated by noise traders then the volatility associated with trading will be negatively related to the adverse selection component of the spread. Next, under the assumption that jumps are due to public information, we can argue that the component of the jump process which is related to trading is due to differences in opinion regarding public information. Since differences in opinion do not lead to information asymmetry, we would expect this component to be negatively related to the adverse selection component of the bid-ask spread. On the other hand, if the volatility is generated by informed investors, it will be positively related to the adverse selection component of the spread. Finally, the jump component that is not related to trading reflects the private information which is not reflected in prices. Therefore, we would expect this component to be positively related to the adverse selection component of the bid-ask spread. I test these alternative hypotheses by using a cross-sectional regression model.

Before we explore the role of public and private information in the determination of stock return volatility, we must first clearly define them. Following French and Roll (1986), public information is the information that becomes known at the same time that it affects stock prices. Examples include the weather, Supreme Court decisions, and the outcome of the

World Series. Information produced by firms, such as financial reports, or by government agencies, such as United States Department of Agriculture crop forecasts, is included in this category if no one trades on the information before it is released. Macroeconomic news, such as the money supply, consumer price index (CPI), producer price index, unemployment rate, and industrial production are also examples of public information. Private information is at the other end of the spectrum. While public information affects prices before anyone can trade on it and the price changes instantaneously when the information is released, private information affects prices through only trading. Much of the information produced by investors and security analysts is in this category.

We estimate the adverse selection component of the spread for each security using data from January 3, 1992 to December 31, 1992 and the procedure described by George, Kaul and Nimalendran (1991). Specifically, the adverse selection component for security i, AI_i is given by

$$AIi = SPi - 2\sqrt{-Cov(RDit, RDi(t-1))} \qquad (3.10)$$

where SP_i is the average proportional bid-ask spread for security i, and RD_{it} is the difference between daily transaction price based returns and returns based on the average of the bid and ask prices.

To examine the relative importance of public information, private information and noise, we analyze the relationship between the adverse selection component of the spread and the components of volatility, after controlling for market value and

price levels. I control for market value because George, Kaul and Nimalendran (1991) find that the spread and the adverse selection component of the spread are inversely related to market value. Several studies have also found that the spread is inversely related to price. Therefore we also include 1/price in our model. Finally, price discreteness can lead to significantly biased estimates of volatility and hence on the estimates of the jump-diffusion model. Moreover, low priced stocks are more likely to be affected by price discreteness. Therefore, we exclude from our sample all firms whose average price in the estimation period is less than five dollars. This gives us a sample of 710 firms. The model we estimate is

$$AI_i = \alpha_0 + \alpha_1(\ln(mval))_i + \alpha_2(1/price_i) + \alpha_3\sigma_{i,0}^2 + \alpha_4\sigma_{i,1}^2 * E(NTS_i) + \alpha_5\Delta_{i,0}^2 + \alpha_6\Delta_{i,1}^2 + ei \qquad (3.11)$$

where σ_0^2 is the diffusion volatility that is not related to trading, σ_1^2 is the diffusion that is related to trading, Δ_0^2 is the non-trading related jump variance, and Δ_1^2 is the jump variance that is related to trading. *MVAL* is the average market value of the firm, and *PRICE* is the average price over the sample period.

The *OLS* estimates and *t-ratio* for equation (3.11) are reported in Table 3.6. I find that the *AI* is inversely related to market value, however, the price level has no significant effect. More interestingly, we find that *AI* is negatively related to both components of the diffusion variance. In addition, *AI* is also negatively related to the trading related

component of the jump variance. To protect themselves from losses from trading with informed traders, the market makers would increase the adverse selection component of the bid-ask spread. The empirical results demonstrate a significant negative correlation between the adverse selection component and trading related volatility. This supports the proposition that the trading is dominated by noise traders as opposed to informed traders. Finally, the jump variance that is not related to trading has significant positive relationship with *AI*. This indicates that significant public information is the major source of information asymmetry faced by market makers.

3.5 Alternative Models For Stock Returns

So far we have assumed that for our sample the mixed jump-diffusion model is superior to the pure diffusion model. Further, we have also assumed that number of trades is a good proxy for trading activity. However, we have not conducted a formal test to determine the best model. In this section we conduct formal tests among alternative model for daily stock return dynamics. I consider four different models: Diffusion (*D*), Jump-Diffusion (*JD*), Jump-Diffusion Conditional on the number of trades (*JDT*), and Jump-Diffusion conditional on number of trades and trading volume (*JDTV*). The most general model is where the variance and the Poisson parameter are conditioned on both the number of trades and the volume of trade. This model is given by the jump-diffusion model described in equation 3.9 together with the following conditional variance model

Table 3.6 Determinants of the Adverse Selection Component of the Bid-Ask Spread

Model:

$$AI_i = a_0 + a_1(\ln[mval])_i + a_2(1/price_i) + a_3\sigma_{i,0}^2 + a_4\sigma_{i,1}^2 * E(NTS_i) + a_5\Delta_{i,0}^2 + a_6\Delta_{i,1}^2 + e_i$$

where the adverse selection component is estimated by , AI_i = (*Proportional Bid-Ask Spread*)$-2*Cov^{0.5}(RD_t, RD_{t-1})$ where RD_t is the transaction price based return minus the return based on average of bid-ask prices for day t. $ln(mval)_i$ is the logarithm of the average market value of firm i, $price_i$ is the average of price over the period of March 3, 1986 and December 31, 1991, $\Delta_{i,0}^2 = \lambda_{i,0}[\mu_i^2+\delta_i^2]$, $\Delta_{i,1}^2 = \lambda_{i,1}E(NTS_i)[\mu_i^2+\delta_i^2]$. $\sigma_{i,0}^2$, $\sigma_{i,1}^2$, μ_i,, δ_i^2, $\lambda_{i,0}$ and $\lambda_{i,1}$ are estimates of conditional jump-diffusion model, $E(NTS_i)$ is the expected number of trades for firm i, $i=1, \ldots, 845$.

	Intercept	$mval_i$	$1/price_i$	$\sigma_{i,0}^2$	$\sigma_{i,1}^2$	$\Delta_{i,0}^2$	$\Delta_{i,1}^2$
	8.40	-0.61	4.82	-1.12	-0.21	0.98	-0.62
t-ratio	(6.08)	(-5.81)	(1.35)	(-3.55)	(-3.33)	(2.78)	(-6.83)

$$\sigma^2_{it} = \sigma^2_{i0} + \sigma^2_{i1}(X_{it}) + \sigma^2_{i2}(Y_{it})$$
$$\lambda_{it} = \lambda_{i0} + \lambda_{i1}(X_{it}) + \lambda_{i2}(Y_{it}) \qquad (3.12)$$

where, X is the number of trades and Y is trading volume. The first three models are nested within the general model and can be obtained by appropriate restrictions. Therefore, I can employ the same likelihood ratio test described by equation 3.7 to determine the best model. In Table 3.7 I report the number of firms for which the restrictions are rejected at the 1 percent level. I find that the jump-diffusion model is superior to the pure diffusion model for every firm. Similarly, the Jump-Diffusion conditioned on trading is superior to pure jump-diffusion for every firm. However, the model conditioned on both the number of trades and volume is only superior in less than 22 percent of the stocks. Therefore, the jump-diffusion model conditioned on number of trades appears to be the best model for our sample of firms.

3.6 Summary

In this chapter, I provide a new methodology based on the mixed jump-diffusion model to estimate the relative importance of private information, public information, noise, and trading activity in explaining the daily stock return volatility. I use this methodology to directly estimate the different sources of the volatility for a sample of 845 firms traded on the Nasdaq-NMS system during the 1986-1991 period. Previous studies have analyzed the relative contribution of private and public

Table 3.7 Comparison of Models: Diffusion (D), Jump-Diffusion (JD), Jump-Diffusion Conditional on Number of Trades (JDT), Jump-Diffusion-Conditional on Number of Trades and Trading Volume (JDTV)

Diffusion:

$$R_{i,t} = (\alpha - \frac{\sigma_i^2}{2}) + \sigma_i Z_t ,$$

Jump-Diffusion:

$$R_{i,t} = (\alpha - \frac{\sigma_i^2}{2}) + \sigma_i Z_t + \sum_{j=1}^{q_t} \ln Y_j ,$$

Jump-Diffusion Conditional on Number of Trades:

$$\sigma_t^2 = \sigma_0^2 + \sigma_1^2 X_t ,$$
$$\lambda_t = \lambda_0 + \lambda_1 X_t ,$$
$$R_{i,t}|X = (\alpha - \frac{\sigma_i^2}{2}) + \sigma_i Z_t + \sum_{j=1}^{q_t} \ln Y_j ,$$

Jump-Diffusion Conditional on the number of trades and trading volume:

$$\sigma_t^2 = \sigma_0^2 + \sigma_1^2 X_t + \sigma_2^2 V_t ,$$
$$\lambda_t = \lambda_0 + \lambda_1 X_t + \lambda_2 V_t ,$$
$$R_{i,t}|(X,V) = (\alpha - \frac{\sigma_i^2}{2}) + \sigma_i Z_t + \sum_{j=1}^{q_t} \ln Y_j ,$$

where X_t = the number of trades, V_t = trading volume, Z_t = a standard Wiener process with instantaneous mean and variance per unit time of a and σ_t^2, q_t = a Poisson process with parameter λ_t, $\ln Y_j$ = one member of family of independent and identically normally distributed random and $R_{i,t}$ is adjusted stock returns

Since *D* is a restricted *JD*, *JD* is a restricted *JDT*, and *JDT* is a *JDTV*, a likelihood ratio test is employed to test the restriction:

$$LR = -2(\ln L^* - \ln L),$$

where $\ln L^*$ is the log likelihood evaluated at the restricted estimates, $\ln L$ is the unrestricted log likelihood. *LR* is χ^2 distributed with number restrictions as degrees of freedom. The following table presents the number of firms for which the restrictions are rejected at 1% significant level.

Portfolio	*JD* vs. *D*	*JDT* vs. *D*	*JDTV* vs. *D*	*JDT* vs. *JD*	*JDTV* vs. *JD*	*JDTV* vs. *JDT*
1 (small)	167	168	168	168	168	50
2	169	169	169	169	169	53
3	168	169	169	169	169	30
4	167	169	169	169	169	20
5 (large)	168	169	169	169	169	31

information using variance estimates around week ends, and during days in which the exchange is closed but businesses are open. Other studies have analyzed the variance around days on which the exchanges are open, but investors endogenously choose not to trade. These studies, however, do not provide a direct estimate of the relative contribution of public information when agents endogenously choose to trade. My method provides estimates for private information, public information and noise during trading and non-trading periods.

I find that trading accounts for nearly all the volatility for large firms and a significant portion of the volatility for small firms. Next, discrete price changes or jumps explain 68 percent of the volatility for large firms and 97 percent for small firms. Finally, the adverse selection component of the bid-ask spread is negatively related to both the diffusion and jump process volatility that are related to trading. This indicates that trading is dominated by noise or liquidity traders. On the other hand, the jump process volatility that is not related to trading is positively related to the adverse selection component. This suggests that the jump process volatility that is not related to trading is a good proxy for information asymmetry.

CHAPTER 4
CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

In this dissertation, I investigate the sources of stock return volatility and the relationship between proxies for information flow and conditional heteroskedasticity for stock returns.

First, I estimate GARCH models for 845 stocks traded on the Nasdaq-NMS. The evidence shows that the GARCH model fits the daily stock returns satisfactorily. However, the persistence of the conditional variance of the stock returns is generally smaller than the ones reported by previous studies. The smaller persistence of the conditional variance is due to the use of the returns based on the average of bid and ask quotes. This eliminates the spurious volatility introduced by the bid-ask bounce when transaction prices are used to calculate the returns. To examine the origins of the volatility clustering, the information flow proxies are included in the conditional variance equation of GARCH models. For most of the stocks in the sample, proxies for information flow (the number of trades or trading volume) demonstrate significant power in explaining the conditional volatility. This is consistent with the hypothesis that the GARCH effect is a manifestation of clustering in the flow of information. In addition, I find that both the number of trades and trading volume are significant for more than half of the stocks when they are all put in the conditional variance

equation. Moreover, the stock returns scaled by the square root of trading volume is less skewed than the returns scaled by the square root of the number of trades. These results do not support the hypothesis that trading volume has no information beyond that contained in the frequency of transactions.

To further examine the role of public information, private information and trading in determining the stock return volatility, I employ a conditional mixed jump-diffusion model to estimate their contributions to the volatility. In contrast to the monthly stock returns, daily returns are characterized by significant discontinuities (jumps). Therefore, inferences from financial asset models which are based only on a diffusion process are likely to be biased. In fact, for small capitalization firms, the volatility attributed to diffusion process is a very small fraction. More importantly, I find that for all the firms in the sample, the mixed jump-diffusion model is superior to the pure diffusion model in describing stock returns.

According to models of trading, the impact of information on stock prices depend on whether information is long-lived or short-lived. If information is long-lived, the informed traders can trade strategically which smoothes price innovation. On the other hand, if the information is short-lived, one is likely to observe significant jumps in the price changes. Because informed traders can not take time to trade strategically. In addition, if we assume that private information and noise can only be incorporated into prices through trading, any volatility that is

not related to trading will be due to public information and market imperfection. Under this scenario, we can decompose the volatility into various components.

I find that for small market capitalization firms, nearly all of the volatility is due to jumps, i.e., unanticipated public information. Further, 72 percent of the jump volatility is associated with trading. For the large firms, the public information accounts for about 68 percent of volatility, almost all of it related to trading. Private information and noise account for about 32 percent of the total volatility. The trading related part is about 85 percent.

In contrast to the findings reported by Jones, Kaul and Lipson (1994a), I find that public information causes significant trading and is even a major driving force for trading. This is consistent with the theoretical models proposed by Varian (1989) and Harris and Raviv (1993), which argue that differences in opinion can lead to significant trading even without any information asymmetry.

I also find that public information on large firms is generated at much higher frequency than on small firms. However, the jump size for large firms is smaller relative to small firms. These findings imply that for large firms the information is released to public more quickly but at smaller packets than for small firms.

I also find that the ratio of non-trading to trading related volatility decreases with firm size. This is in contrast to Jones, Kaul and Lipson (1994a). They attribute the positive

relationship between the non-trading to trading volatility ratio and firm size to the fact that there are more investors and market analysts who follow large firms than small firms. Therefore, it may be easier for agents to decipher and agree upon the implications of certain types of public events for such firms. And prices of large firms may move more easily without trading. My interpretation is that the fact that more investors and analysts who follow large firms would lead to more diversified opinions on the implications of the same piece of information. Also, having more analysts and investors generates more private information. Therefore, the trading driven by the private information is higher.

Over all, the evidence from this study indicates that trading is dominated by noise trading and by differences in opinions. This suggests that the volatility of the stock market may not reflect a rational response to information arrival.

Finally, there are several issues that should be addressed in future research. In this study, especially for the mixed jump-diffusion model, I assume that the information arrivals are independent. However, the sequential information arrival hypothesis implies that the information arrival may be autocorrelated. Therefore our results may be biased. The model can be improved by employing a mixed jump-diffusion with an explicit autocorrelation specification in the jump process as well as the diffusion process to address this issue. Further, higher frequency data series (e.g., data for each transaction

and quotes) can be utilized to obtain additional information about the sources of stock volatility.

Another potential bias is introduced by discrete price quotes. The institution of the stock exchanges requirement restricts stock prices must be quoted by the multiples of 1/8. For firms with lower stock prices, continuous changes may be misidentified as jumps. Also, if new information arrives but is not significant enough, price may not change due to the price discreteness. The specification of the models in this study can give biased estimates. A probit model should be considered to solve this issue.

The information contents of the trading volume and the number of trades are overlapping but there exists significant difference. As shown in this study, the number of trades is more effective in explaining the kurtosis while the trading volume explains the skewness better. Intuitively, the number of trades is a better proxy to the arrivals of information. However, the trading volume would shed more insights on the quality of the information and the investors' confidence. A sophisticated theoretical model is needed to further explore this matter.

I find the private information does not play the primary role in the volatility of the diffusion process. However, I can not identify its contribution to the volatility more closely. Much work remains to be done in this area.

APPENDIX
BOOTSTRAP TECHNIQUE

To calculate the standard error of the sample median estimates of each portfolio, I simulate the empirical CDF of median estimates for each portfolio by resampling with replacement from 169 firms, and repeat the sampling 500 times for each of 500 random independent replications for each portfolio. The stand error of the median is computed based on the new "median" sample of 500. For more details see Efron and Tibshirani (1986) and Jones, Kaul and Lipson (1994a).

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BIOGRAPHICAL SKETCH

Min Zhu holds degrees in management science from the University of Science and Technology of China, and economics from Fudan University. He earned a certificate of achievement from the Ford Foundation graduate training program in economics at the People's University of China. This achievement led to a two-year position with the Ford Foundation training program at Fudan University. His main research interests include econometrics, stock market microstructure, game theory, and international trade. His research has been published in *World Economy Forum* and *Games and Economic Behavior*. Min Zhu is a Ph.D. candidate in the Department of Economics at the University of Florida, where he expects his degree to be conferred in August of 1996.

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

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